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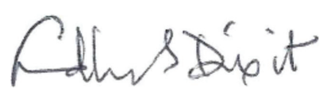
From the Desk of the Editor-in-Chief

Dr Sudhir Dixit
Editor-in-Chief

We are delighted to present the third issue of *Wireless World Research and Trends* (WWRT) magazine. Building on the solid foundation laid in the first two issues, this issue features seven exciting articles on trending topics, from AI/ML in communication systems to applications and services such as IoT, edge computing, SDN, and more.

This issue includes seven articles, with a special Experts Column, a regular feature of the magazine akin to an op-ed by an expert. In this issue, the column is authored by Prof. Merouane Debbah from Khalifa University in the UAE. The first article explores the co-evolution of AI and 6G, and for the first time in the literature, identifies the mutual requirements for both that support each other. Given the emphasis on green communication systems, especially in the mmWave bands, the second article focuses on the design and analysis of mmWave antennas for New Radio in 5G systems. In the third article, the authors propose an SDN-enabled, energy-aware routing framework that provides a scalable and sustainable solution for real-time energy management in circular industrial ecosystems. The fourth article applies deep learning techniques, specifically the ResNet-50 architecture (a deep convolutional neural network (CNN) architecture) integrated with U-Net, to accurately detect and segment cloud cover from satellite imagery, commonly used by researchers and developers in remote sensing and related fields. In the fifth article, the authors apply machine learning techniques to detect anomalies in WBANs, focusing on One-Class Support Vector Machines (One-Class SVM) to address common sensor issues, such as malfunction, external interference, or cyberattacks. With the arrival of AI/ML applications in speech and imaging, there is growing interest in analyzing emotions and fluency from speech and images/videos. Thus, the sixth article covers exactly these topics. The seventh and final article discusses harnessing the potential of machine learning for mental health, specifically predicting depression using diverse data sets.

I hope you find these articles engaging, and I welcome your comments and feedback. As an open-access journal that aims to include all researchers and practitioners, we also invite inquiries and proposals to guest-edit future issues. Happy reading!



Will 6G Become the Global Standard for Mobile AI Agents?

Prof. Mérouane Debbah,
Director of the 6G Research Center at Khalifa University

The Rise of Autonomous AI Agents

We stand at a new frontier in computing: the rise of autonomous AI agents. Powered by large language models (LLMs), these agents can plan, reason, and even collaborate with one another to accomplish complex goals. From coordinating supply chains to personal digital assistants negotiating our schedules, multi-agent AI systems are quickly moving from science fiction to practical reality. Early experiments show that when multiple LLM-based agents team up, they can solve problems no single model could handle alone. In fact, developers are already leveraging such agent collaboration to automate workflows and create intelligent experiences. This trend has sparked an urgent question: *how* will all these AI agents communicate, and are today's networks and protocols prepared for an AI-to-AI world?

Patchwork Protocols: MCP, ACP, and OASF

Recognizing the need for agent-to-agent communication, the tech community has begun crafting new protocols and frameworks. One example is the Model Context Protocol (MCP) – a proposed standard that started as a way to feed tools and context to LLMs, but has evolved to support agent-to-agent interactions as well. MCP provides fundamental capabilities like authentication, capability negotiation, and context sharing between agents. In parallel, other researchers introduced an Agent Communication Protocol (ACP), aiming to let agents from different platforms talk in a common language. ACP handles the main issues of inter-agent messaging – authentication handshakes, session setup, exchanging results or errors – so that an agent built in one framework can communicate with another built in a different framework. Complementing these is the Open Agent Schema Framework (OASF), a kind of "DNS for agents" that provides a standard format to describe an agent's identity and capabilities. OASF would allow a directory of agents where any agent can discover what other agents can do, regardless of vendor or platform.

Other efforts are emerging too. For example, Google's proposed Agent-to-Agent (A2A) protocol was designed to enable agents to delegate tasks across the internet. A recent survey highlighted how these pieces fit together: MCP standardizes how LLM-based agents access data/tools, ACP coordinates agent teams in a local environment, and A2A enables collaboration among agents across different ecosystems. The takeaway is clear – whether it's through open-source initiatives or corporate R&D, there's a patchwork of protocols being built to fill the communication gap between AI agents. These are promising first steps, but they remain disparate. We lack the equivalent of a unifying "TCP/IP suite" or a universal language for AI agents.

Internet and 5G: Built for Humans, Not AI

Why not just use existing internet standards? The truth is that today's communication protocols and networks were not designed with AI-native communication in mind. The internet we use was engineered for human-driven information exchange: web pages retrieved via HTTP, email via SMTP, videos streamed over RTP. These protocols assume relatively simple request-response patterns and human consumption speeds, not the rapid-fire, context-heavy back-and-forth that AI agents will require. Yes, we do have machine-to-machine (M2M) and IoT protocols, but those typically carry simple sensor readings or commands – nothing like the cognitive negotiations autonomous AI agents might engage in.

Moreover, current wireless networks (like 4G/5G) were optimized for human-centric traffic (think video calls, browsing) and known IoT use cases. They weren't built to handle swarms of AI agents continuously exchanging high-dimensional data and reasoning with each other in real time. Future AI agents might need to share intermediate reasoning steps, negotiate plans, or jointly learn from data, all on the fly. This demands ultra-low latency and extreme reliability beyond what today's mainstream internet guarantees. While 5G provides lower latency and network slicing, it still treats AI and edge computing as an add-on. As one industry analysis put it, in 5G, AI is mostly an overlay, whereas 6G aims to deeply embed AI into the network's core – making it *"AI-native"* rather than an afterthought. If we try to force-fit AI agent communication into the existing Internet paradigm, we risk severe inefficiencies. Imagine millions of GPT-based agents all calling APIs and waiting on HTTP responses – the overhead would be enormous. AI agents need a communication fabric that moves **as fast as they think.**

6G: A Network for AI Agents

The design of next-generation wireless network is currently in research labs (including mine) around the world. More than just "5G but faster," 6G is being envisioned as a radical upgrade that could make AI a first-class citizen in the communications realm. What does this mean? For one, 6G targets latency on the order of microseconds, not just a few milliseconds. This kind of near-instantaneous responsiveness is exactly what autonomous agents coordinating in real time will demand. 6G also promises higher reliability (six-nines and beyond) and greater capacity, so networks can support an explosion of machine-generated traffic. Just as importantly, 6G is likely to blur the line between communication and computation – bringing cloud-like processing and AI model hosting *into* the network itself (at base stations, edge servers, etc.).

In my view, 6G isn't just another network upgrade; 6G is the gateway towards AGI (artificial general intelligence). That might sound hyperbolic, but consider what 6G enables: *"developing the distributed real-time communication and computing fabric infrastructure to connect intelligence and enable AI agents to interact in a seamless way"*. Those are words I shared in a recent panel, and I firmly believe them. With semantic-level connectivity and integrated sensing, 6G networks could allow AI agents to share not just data, but meaning – a concept known as semantic communications. Instead of sending raw video, an AI security drone could send an alert like *"intruder at Sector 5, confidence 90%"* to another agent, saving bandwidth and time. 6G's native AI integration might even let agents access on-demand AI processing along their communication path. Imagine you need a quick summary of data before passing it on? A 6G node might handle it via an embedded AI service. In short, 6G could become the *de facto* platform for agent-to-agent communication – a network where human and AI traffic coexist, but where the AI portion is optimized at the protocol level for machines talking to machines. 6G's architecture could provide built-in coordination mechanisms for agents. For example, a 6G base station might act as a local broker between AI agents in its cell, mediating their messages, ensuring security and identity verification, and caching shared knowledge. This kind of functionality at the network level would be extraordinarily hard to achieve with today's overlay networks.

Toward an "HTTP" for AI Agents

While 6G can offer the raw power and intelligent infrastructure, we still face a major gap: the lack of a universal protocol or language for AI agents to communicate. History has taught us that standardization can ignite revolutions. The World Wide Web took off only after Tim Berners-Lee introduced HTTP and HTML – open standards that let any browser talk to any server, creating a single web out of many disparate networks. In the realm of AI agents, we haven't yet had our "HTTP moment." Instead, we see many parallel efforts (MCP, ACP, A2A, etc.) and proprietary APIs. For the agent economy to truly flourish, we need to converge on common, open protocols. Imagine an "Agent Communication Standard" that is to AI agents what HTTP is to web pages – enabling discovery, negotiation, messaging, and collaboration in a consistent way. This doesn't mean scrapping the great work done so far; rather, it means building on it and generalizing it for all. It's encouraging to see early moves in this direction: for instance, the MCP initiative is gaining traction as a possible building block of such a standard, with contributions from Amazon, Google, and an array of startups.

What might an "HTTP for agents" entail? It would likely need to handle richer dialogues than request/response – perhaps a sequence of messages (a negotiation, a brainstorming session between two AI, etc.). It would require semantics for things like capability discovery and for goal negotiation. There's also the question of trust and safety: an agent protocol might include built-in authentication, so agents can verify each other's identities and even reputation scores, before cooperating. Security will be paramount – we don't want open agent channels to become the next vector for malware or misinformation. Luckily, we have decades of experience securing human internet traffic that can inform agent communication security as well. The key point is that by defining standard *methods* and *formats* for agent interactions, we remove friction. Any compliant agent could, out-of-the-box, talk to any other, just as your web browser can open any website thanks to HTTP.

What should be in our agenda?

The time to act is now. 6G development is in full swing, with global initiatives hammering out standards that will define our wireless future. At the same time, the AI world is moving fast – new autonomous agent frameworks emerge almost monthly. This is the critical moment for academia, industry, and standards bodies to come together and ensure that AI-native communication doesn't get left as an afterthought. We should begin by convening joint workshops and working groups between the key players: telecom engineers who design 6G's architecture, AI researchers who design agent algorithms, and international standardization organizations (ITU, 3GPP, IEEE, W3C – all have a stake). The goal should be to craft a blueprint for an Agent Communication Standard robust enough to be adopted at global scale. That might mean extending existing protocols or creating something entirely new – but in either case, it must be open and agreed upon.

In parallel, we need more research like the work my team is doing: exploring how multi-agent AI systems perform on advanced networks, and what novel requirements emerge. For example, our early findings on emergent behaviors in multi-agent systems show that agents can even develop their own communication codes if left to it. Rather than letting a thousand incompatible "agent dialects" bloom in isolation, we should guide this process to converge on a shared language from the start. It's reminiscent of the Tower of Babel myth – if each AI agent cluster speaks a different tongue, collaboration at scale becomes impossible. A new standard can be the universal language that avoids that fate.

Finally, I call on the industry's visionaries – many of whom read *Wireless World Research and Trends* – to be bold in this arena. The creation of an AI agent communication standard (and the integration of it into 6G networks) is a moonshot challenge, no doubt. It will require competitors to cooperate and regulators to move at the pace of innovation. But the payoff would be extraordinary: a seamless global agent ecosystem where AI agents can truly interoperate, unleashing a new wave of productivity and capabilities. Just as HTTP unlocked the Web and TCP/IP unlocked the Internet, a new 6G A2A (Agent-to-Agent) protocol could unlock what I'd call the Mobile Internet of Intelligent Agents.

So do we need a new standard for AI agent communication? The answer is *yes*. And the follow-up question – will it be 6G? –

I would argue *6G will be a big part of it*. 6G offers the connective tissue and performance that make an AI-native standard feasible. Now it's on us – researchers, engineers, policymakers – to design that standard and make it real. The autonomous agents are coming online, and they'll need to talk. Let's give them a common language and an optimized channel to do so. The future "conversation" of our AI agents should be as interoperable and ubiquitous as the Web – and if we achieve that, we truly step into a new era of connectivity and intelligence.

Biography

Mérouane Debbah is Professor at Khalifa University of Science and Technology in Abu Dhabi and founding Director of the KU 6G Research Center. He is a frequent keynote speaker at international events in the field of telecommunication and AI. His research has been lying at the interface of fundamental mathematics, algorithms, statistics, information and communication sciences with a special focus on random matrix theory and learning algorithms. In the Communication field, he has been at the heart of the development of small cells (4G), Massive MIMO (5G) and Large Intelligent Surfaces (6G) technologies. In the AI field, he is known for his work on Large Language Models, distributed AI systems for networks and semantic communications. He received multiple prestigious distinctions, prizes and best paper awards (more than 50 IEEE best paper awards) for his contributions to both fields. He is an IEEE Fellow, a WWRF Fellow, a Eurasip Fellow, an AAIA Fellow, an Institut Louis Bachelier Fellow, an AIIA Fellow and a Membre émérite SEE. He is actually chair of the IEEE Large Generative AI Models in Telecom (GenAINet) Emerging Technology Initiative and a member of the Marconi Prize Selection Advisory Committee.

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Quantifying the Mutual Requirements Driving AI and 6G Co-Evolution

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Abstract: This paper studies the mutual requirements of artificial intelligence (AI) and sixth-generation wireless networks (6G) as they evolve together. Unlike previous wireless network generations, which added AI after deployment, 6G aims to be AI-native by embedding intelligence into its core design, interfaces, and operations. We analyze how advanced AI, such as generative AI (GenAI) and large language models (LLMs), create strict requirements for 6G networks, including low latency, high bandwidth, efficient resource usage, scalability, security, and compliance with regulations. Additionally, we identify key features that 6G networks need to support for efficient AI, such as distributed AI training, inference capabilities, dynamic resource management, programmable interfaces, and intelligent orchestration. By examining specific use cases like AI Training as a Service and LLM-based network management, the paper provides measurable insights into important performance indicators. This analysis serves as a practical guide for designing and standardizing future 6G networks optimized for AI-driven services.

Keywords: 6G networks, artificial intelligence, generative AI, large language models, network for AI, AI for network, quality of service.

1. Introduction

The co-evolution of artificial intelligence (AI) and sixth-generation cellular networks (6G) constitutes a foundational phase in the digital infrastructure, in which we are witnessing an era where connectivity and intelligence are converging at the system, architectural, and operational levels. Unlike previous wireless generations, where AI was an add-on applied post-deployment to optimize isolated functions, 6G is being designed as AI-native from the ground up, embedding AI into the core architecture, interfaces, and service models. While AI is expected to play a central role in enhancing the design, deployment, and operation of 6G networks, the opposite is equally important, in the sense that 6G should be purposely designed to support the stringent requirements of advanced AI workloads, including among others, federated learning (FL), generative AI (GenAI) applications, etc.

A recent industry report shows that Telcos anticipate over 20% gains in revenue or cost efficiency through AI adoption, particularly in domains such as network operations, customer service, and software development [1]. AI use cases such as network capacity planning, field service assistance, and automated code generation, to name a few, are already making a notable impact in the telecom sector. However, the deployment of AI at scale introduces new pressures on the network itself, requiring 6G systems to evolve to meet new expectations of ultra-low latency, distributed intelligence, dynamic resource allocation, and energy-efficient operation [2].

This two-way relationship, AI for Network and Network for AI, requires a fundamental shift in network design. To illustrate, while AI can be utilized to optimize handovers, network behavior, resource allocation, etc., the network itself must enable programmable interfaces, reliable compute nodes, and data processing pipelines that enable distributed AI training and inference. Emerging concepts, such as AI-as-a-Service and LLM-driven orchestration, further explain how 6G will not only serve as an AI-optimized communication fabric but also as a native computational platform for serving AI workflows [3].

The aim of this paper is to characterize, in a quantitative manner, the two-way relationship between AI and 6G, AI for Network and Network for AI, by identifying the infrastructure and system demands that advanced AI workloads, such as large language models, generative AI, and distributed learning, impose on 6G networks. In parallel, we will articulate the enabling capabilities that 6G must deliver to effectively support, accelerate, and scale the deployment of AI across diverse use cases. This includes examining performance requirements such as latency, bandwidth, energy efficiency, and data accessibility, which are essential for realizing the full potential of AI-driven services in next-generation networks.

2. Measuring the Impact of AI in 6G

Although the extent of the impact of GenAI models in telecom networks in the following years is not measurable yet, several recently published studies have presented the expected and most relevant GenAI use cases [4]. A recent survey, based on data from 104 senior-level respondents from 73 communication service providers (CSPs), has identified seven families of use cases which are either being explored already today, or have short- to mid-term

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Table 1.

Families of GenAI use cases for mobile network operators (MNOs) [5]	
Family	**User Cases**
Customer operations	Customer chatbot, call center agent documentation and coaching, website assistance, and predictive and personalized services.
Sales & marketing	Marketing collateral generation, personalized customer/email scripts, social media automated responses.
Network	Field service operations guided assistance, network/capacity planning, network security testing, post-mortem creation, root cause analysis.
IT/software engineering	Automated code generation and testing, automating repetitive tasks, detection of code security vulnerability.
Product innovation	Carrier billing, personalized services, voice value-added services, business-to-business, customer call services.
Internal knowledge, training & development	Evaluating new trends/developments, competitive analysis, and supply chain analysis.
Business operations	Contract, Fraud management, partner management, human resources.

potential [5]: Customer operations, sales and marketing, network, information technology (IT) and software engineering, product innovation, internal knowledge, and business operations. These families of use cases are illustrated in Table 1.

An analysis has been published presenting how GenAI models could help telcos to improve their revenues, based on a response from 130 telco operators [1]. This report identified five use case categories: customer service, sales and marketing, network, IT and support functions. Specifically, for network applications, GenAI models optimize coverage, capacity, and bandwidth, enhancing planning efficiency. They also streamline the launch of new services through efficient configuration, testing, and tuning. Finally, GenAI aids network management and orchestration by quickly resolving issues and coordinating resources, thus improving network reliability and stability [6].

2.1. Business Value of the Use Cases

Table 2 illustrates the expected impact of GenAI models per business domain of use cases [1]. This table highlights that more than 85 percent of the executives attribute to GenAI models more than 20 percent revenue or cost savings impact by business domain. Importantly, customer service, together with marketing and sales, makes up the largest share of the total impact expected in terms of business value. For instance, [1] reports that AI chatbots are anticipated to improve customer support efficiency in customer service, potentially reducing related costs by 15 to 20 percent. Additionally, using GenAI models to summarize voice and written client interactions is expected to reduce associated costs by up to 80 percent.

In marketing and sales, MNOs use GenAI for personalized messaging, achieving over 10% customer conversion rates. GenAI also enhances network planning by structuring component data and helps IT developers double their coding productivity [7]. Support functions anticipate 30% productivity gains. Another report [8] highlights GenAI usage by telecom professionals: 57% for customer support and productivity, 48% for network management, 40% for network design, and 32% for marketing content.

2.2. AI Training as a Service in 6G Networks

In future telecommunication networks, data is generated through different sources and collected by sensors, cameras, radars and Lidars on various terminals. At the same time, with the rapid development of high-end terminals, exploiting distributed on-device processing capabilities opens the door for new AI-added-value services. In this case, 6G can provide AI training as a service in a collaborative and efficient manner by connecting data silos to enable powerful AI model production. In our vision, AI training as a service encompasses use cases for both AI for Network and Network for AI. In AI for Network, AI/machine learning (ML) models enhance network functions, while in Network for AI, networks monetize their resources and capabilities (e.g., data collection and storage) by offering AI training services to consumers through dedicated interfaces.

Figure 1 shows a high-level description of AI training as a service use case. Collected data can be transferred to the network side, where datasets are built up and used to generate powerful AI models in a centralized way. An alternative is training AI models locally instead of uploading the local raw data to the central processing centre. Making choice between the centralized or the distributed way about AI model training depends on several considerations [9, 10]. First, the decision considers the processing capabilities of the involved training entities. Second, the privacy protection of the local data should be ensured. Finally, the resources for training the AI model should be optimized.

2.3. AI Inference as a Service in 6G Networks

The rapid diffusion of AI in our society is allowing the development of numerous applications across individuals, industry, and public organizations. In our vision, 6G networks, enhanced with intelligent decision-making, will serve as a platform for delivering AI-based services. In this case, the networks can provide AI inference as a service in a collaborative and efficient manner. As for the AI training as a service, AI inference as a service is a family of use cases for both AI for Network and Network for AI.

Figure 2 illustrates three AI inference scenarios in 6G networks. In Figure 2(a), the network manages the entire AI inference workload, requiring data preprocessing to reduce latency and address privacy concerns. AI inference may be distributed across network nodes based on factors like distance and resource availability, though this introduces challenges in synchronization, security, and communication overhead. Figure 2(b) depicts AI

Table 2.

GenAI models impact on telcos by use cases [1]			
Business Domain	**Share of Total Impact (%)**	**Share of Business Leaders by Domain (%)**	**Example User Cases**
Customer operations	35	85	Customer-facing chatbots, call-routing performance, agent copilots, bespoke invoice creation.
Sales & marketing	35	45	Content generation, hyper-personalization, copilots for store personnel, customer sentiment analysis and synthesis
Network	15	62	Network inventory mapping, network optimization via customer sentiment analysis, self-healing via customer sentiment analysis on network problems.
IT	10	55	Copilots for software development, synthetic data generation, code migration, IT support chatbots.
Support Functions	5	10	Procurement optimization, workplace productivity, internal knowledge management, content generation HR Q&A.

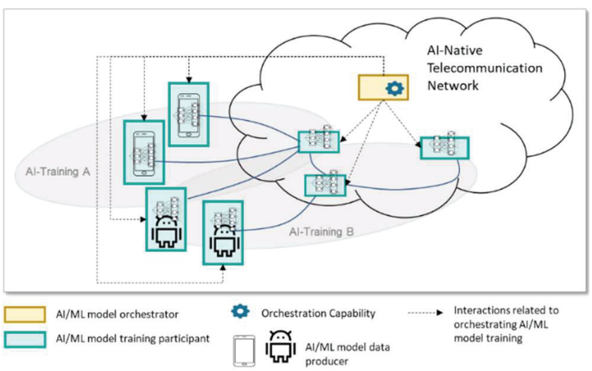

Figure 1.

AI Training as a Service. AI-Training A and AI-Training B represent two instances of the AI Training as a Service.

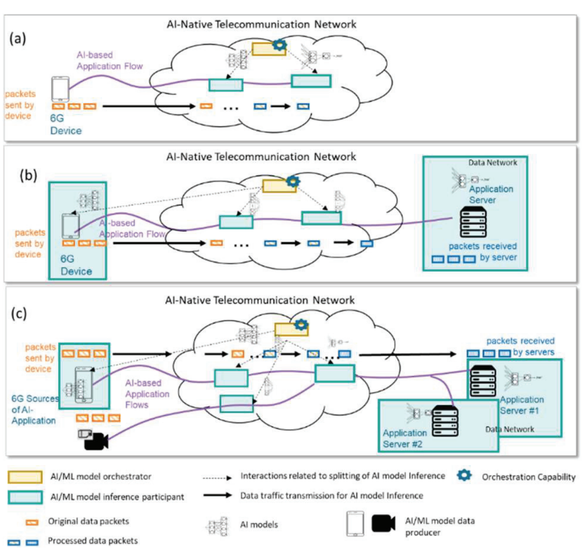

Figure 2.

AI inference as a service.

inference split across the network and its environment, including users, devices, and applications. Processing part of the AI model at the user device (UE) minimizes communication needs and enhances privacy, as only processed data features are transmitted to the network. Figure 2(c) presents AI inference offloaded to the network, where an AI-enabled application accesses data from multiple sources and delivers results to multiple consumers. AI-Agents handle specialized processing, supporting applications like multi-stream fusion, while the network intelligently coordinates data sources, AI-agents, and nodes to optimize performance.

2.4. LLMs in 6G Networks

Large language models (LLMs) are advanced AI models capable of processing information and generating human-like text. In 6G networks, they offer three key capabilities that enable value-added services [11]:

- Semantic capabilities: LLMs develop an internal representation of textual data in the form of real-valued vectors called embeddings. LLMs can process and comprehend intricate information, such as the content within standard documents and infer logical conclusions from the given inputs.
- Intelligent Access to Knowledge: By understanding the specific intention conveyed through the prompt, an LLM can effectively apply its knowledge base to craft a response tailored to the user's needs.
- LLMs as Orchestrators: LLMs can utilize their knowledge to deconstruct complex tasks into manageable subtasks and deploy suitable (external) tools for each, as illustrated in Figure 3.

Integrating LLMs into 6G networks enhances AI for Network by leveraging extensive textual data, including network anomaly tickets, product manuals, and software documentation. This supports the full network lifecycle, covering planning, design, implementation, and optimization (see Figure 4). In Network for AI, 6G facilitates LLM-based AI agent coordination, model transfer, and distributed training while providing essential data collection for model development. AI agents interact with the network environment through task-specific AI capabilities for data collection, resource access via APIs, and decision dissemination.

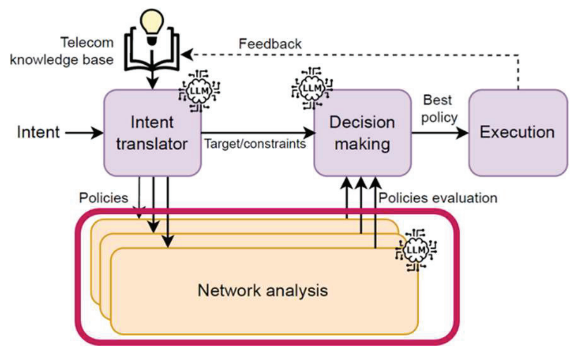

Figure 3.
LLM based intent-driven network [12].

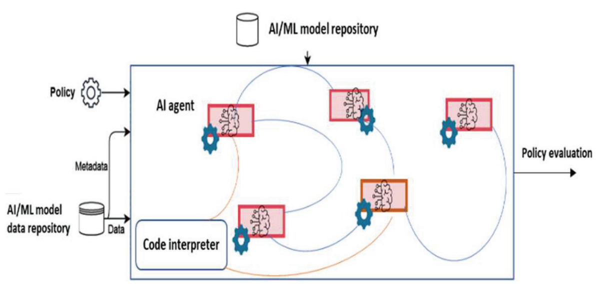

Figure 4.
AI agents for network policy evaluation.

3. 6G Functional Requirements Shaped by AI

The next generation of AI, especially artificial general intelligence (AGI), is expected to play a significant role in the design, development, and operation of 6G technologies [13]. In contrast to previous generations of wireless systems, where AI was typically integrated post-deployment primarily as a tool to enhance specific functions (e.g., traffic prediction and resource allocation) [14], 6G is conceived as a fundamentally AI-native infrastructure. In this new paradigm, telecom networks will leverage AI for interacting with their environment, enabling novel value-added services, and enhancing the performance of networks and services. To realize this vision, the 6G network will host new functions and interfaces to fully support the ML model lifecycle as well as the joint optimization of connection, data collection and processing, algorithms, and models in the AI-native telecommunication network and its environment.

3.1. Data Management

The 6G network will natively support comprehensive data lifecycle management for AI training and inference, covering data collection, transmission, processing, storage, and consumption. Specifically, 6G networks will:

- Enable flexible data collection across resources, networks, and services at varying time granularities.
- Optimize data processing to enhance format compatibility, data quality, privacy, and security tailored for AI applications.
- Facilitate robust data management to support AI training, testing, and validation processes.
- Establish and maintain knowledge bases to enable retrieval Augmented Generation (RAG) capabilities [15].
- Ensure regulatory compliance for obtaining, storing, and processing private user data [4].
- Leverage user data and network-controlled information to provide innovative AI/ML-driven value-added services.

3.2. Resource & QoS Monitoring

Continuous resource and quality of service (QoS) measurements are the basis in 6G networks for successful and cost-effective AI service provisioning. Importantly, the following functions and interfaces should be introduced or enhanced:

- Functions for monitoring the status of AI resource usage.
- Function for monitoring the AI service performance requirements, such as AI model accuracy, AI service latency, or AI service density (i.e., the number of AI models operating within a given area).

3.3. 6G Interfaces for LLMs and AI Agents

To fully leverage LLMs' semantic, orchestration, and knowledge-access capabilities, 6G networks should support interfaces exposing LLMs to:

- Knowledge bases.
- Business intents.
- Network operator policies.
- Network resource availability, user QoS, and KPIs.
- Coordination among AI agents.
- Tools such as search engines, databases, and devices.

3.4. Resource Optimization

6G networks need to jointly consider the requirements of AI value-added services together with the requirements of other (e.g., connectivity) offered services and optimize resource allocation accordingly. To achieve this goal, 6G networks integrate mechanisms and support functions for:

- Prioritizing requirements between AI Training services and other services offered by the network, considering joint communication and AI resources.
- Benchmarking available AI models with respect to a target AI service, for example, by generating and running tests to assess the service required capabilities.[1]
- Determining the AI model and its configuration for a requested service offered by the 6G network. This task shall take into consideration the status of communication and AI resources.

[1] AI capabilities may include, but are not limited to, decision-making, reasoning, forecasting, clustering, classification, self-learning, acquiring contextual information, natural language processing, and complex tasks decomposition.

3.5. Resource-aware Model Training and Inference

AI consumes a notable amount of resources, including data and computers. In addition, AI/ML applications usually leverage different AI/ML models to perform the same task under different conditions with the intention to select the most accurate result [16].

6G should integrate in a native manner the capability to adapt AI models and the entire model lifecycle, including data collection and model download, to time-space varying available network resources. To attain this objective, the following mechanisms and related functions are expected:

- Intelligent mechanism for dynamically splitting the AI training and inference workload between the 6G network and its environment, based on resource availability.
- Intelligent AI training mechanism that constructs AI models able to work in different configurations to trade-off AI service performance with network resource usage [17].
- Intelligent mechanism to transfer additional layers of AI models to the inference endpoint to increase the model performance upon changes in the network conditions and AI service requirements [17].

4. 6G Performance Requirements Shaped by AI

6G systems will provide new added-value services integrating AI and leveraging telecommunication network communication and computing capabilities. Specifically, AI for Network refers to services that optimize the telecom network performance by employing AI/ML on network-specified functionalities and capabilities. This shift represents an incremental improvement in network planning strategies and a transformative advancement, providing 6G networks with real-time, autonomous decision-making, self-healing, and ubiquitous human-machine interactions. In addition, Network for AI refers to services that provide network support for AI/ML-based applications and services, such as training and inference. These newly added value services based on AI necessitate 6G networks to handle significant amounts of real-time data and adapt to changing conditions.

4.1. Ultra-Low Latency

Ultra-low latency (less than 1 millisecond) is a major requirement for AI applications that demand instant decision making, such as coordinating autonomous vehicles, performing AR surgery in real-time, and completing in-flight predictive maintenance for aviation systems [18]. To achieve this, 6G systems need specialized hardware capable of fast AI processing directly at the network edges. For instance, embedding neural processing units (NPUs), which are a type of processor optimized explicitly for handling AI tasks quickly and efficiently, in 6G base stations (BSs). Consequently, AI processing occurs closer to the users and devices, significantly reducing delay. Moreover, strict QoS policies must be established specifically for these critical AI services. To enforce QoS policies, deterministic network protocols, such as IEEE 802.1 time-sensitive networking (TSN), can be employed to ensure predictable and reliable latency even in heterogeneous networks with many connected devices. In addition, adopting new wireless waveforms and ultra-wide frequency bands will make signal delays negligible. Meeting these ultra-low latency demands ensures 6G will support current AI applications and enable future AI scenarios with even stricter real-time requirements.

4.2. Resource-Efficiency

The growing use of large-scale AI workloads is a serious energy consumption problems that arise when deployed at scale. For instance, an implementation of an advanced LLM, such as GPT-4, can consume energy equivalent to that of 100 average households in a year [19]. This high energy demand necessitates integrating energy-aware design into 6G architectures. Consequently, 6G employs neuromorphic computing methods, including spiking neural networks (SNNs), and hybrid energy harvesting, such as solar-powered nodes, to align processing with renewable energy availability and delay tolerances [20]. Moreover, Algorithmic and system-level optimizations further boost energy efficiency.

Techniques like model quantisation, structured and unstructured pruning, and network architecture search reduce parameter redundancy and computational complexity in resource-constrained wireless environments [21]. Data-centric strategies like selective sampling and prompt engineering also cut unnecessary computations while preserving model fidelity. Additionally, energy-aware network slicing enables operators to allocate resources, such as bandwidth and computing power, based on real-time carbon intensity data [22]. Collectively, these measures position 6G as a vital platform for sustainable AI deployments.

4.3. High-Bandwidth

6G networks operate in terahertz (THz) frequency bands (0.1–10 THz) with transmission rates exceeding 1 terabit per second (Tbps) [23], enabling advanced applications like tele-holograms, real-time multi-sensor fusion for autonomous vehicles, and distributed AI model development. For example, autonomous vehicles using lidar, radar, and 8K cameras generate 10–20 Tbps of raw data per hour [24], requiring efficient transmission to edge servers for immediate, safety-critical processing. Similarly, smart-city digital twin networks synchronize petabytes of urban sensor data, pushing THz-based networks to their theoretical maximum throughput. However, AI implementation at THz frequencies faces challenges due to atmospheric absorption and environmental blockage, limiting practical transmission distances to about 10 meters. To overcome these constraints, 6G incorporates AI-driven techniques such as reconfigurable beamforming, real-time channel estimation, and adaptive resource allocation. By enabling intelligent network management, AI transforms 6G bandwidth from a static resource to a dynamically optimized system, ensuring data-intensive AI applications achieve over 1 Tbps throughput while meeting stringent latency and energy efficiency requirements for next-generation wireless technologies.

4.4. Scalability

Successfully integrating AI into 6G networks requires overcoming the limitations of centralized cloud architectures, especially with over 50 billion connected devices expected by 2030. To address these challenges, distributed AI processes data across multiple edge nodes, enhancing both scalability and privacy. Specifically, it enables parallel processing, which is essential for applications like autonomous vehicle coordination, industrial asset tracking, and augmented reality, each demanding local and distributed computing. Moreover, FL further strengthens privacy by allowing edge devices to train models locally without transmitting sensitive data, thereby improving response times and reducing network load. Additionally, hierarchical and hybrid FL models optimize bandwidth and computational efficiency by aggregating updates at intermediate nodes. Furthermore, AI-driven middleware platforms coordinate distributed AI tasks, ensuring balanced workload distribution across diverse hardware environments. Meanwhile, autonomous AI and decentralized multi-agent reinforcement learning (MARL) enhance resource allocation and enable dynamic network responsiveness. Ultimately, by prioritizing scalability and privacy, distributed AI empowers 6G networks to efficiently support AI-driven advancements.

4.5. Security and Privacy

The integration of AI into 6G networks introduces critical security and privacy challenges due to the complexities of large-scale distributed systems [25]. AI-driven edge architectures are vulnerable to adversarial, model inversion, and data poisoning attacks due to their accessibility and distributed nature [26]. AI-based security protocols evolve into advanced solutions, such as anomaly detection, automated attack response, and adaptive trust management, enhancing resilience. AI is also expanding the scope of privacy, as its implementation will necessitate the use of privacy-preserving frameworks. Collaborative AI methods will require alternative privacy-preserving techniques (e.g., differential privacy, secure multi-party computation, and homomorphic encryption) in which sensitive user data can be safeguarded when learning is decentralized. In summary, AI not only identifies important security and privacy issues, but also shapes and informs the framework under which security solutions and privacy-enhancing technologies are developed, ultimately ensuring trusted, secure, and robust 6G deployments.

4.6. Ethical and Regulatory Compliance

With the widespread use of AI for autonomous control of critical network functions in 6G, there are compelling ethical issues and regulatory compliance issues which need to be carefully addressed. AI-based decision-making will have a significant impact on essential network functions, such as resource allocation, management of access to the network, and priority of service decisions. As ethical issues of fairness, accountability, transparency, and non-discrimination come to bear open AI-based network decision-making, explainable AI (XAI) is crucial and valuable. XAI produces interpretable and transparent explanations for AI-based decisions, enabling auditing, promoting trust for users, and promoting accountability for network operators. Moreover, the pervasive application of AI within 6G networks compels regulatory bodies to develop adaptive, continuously updated compliance frameworks. These frameworks must comprehensively address data privacy, security risks, and broader societal impacts resulting from AI integration. By explicitly embedding ethical considerations and regulatory compliance into AI systems and practices, 6G networks can ensure socially responsible and equitable technological advancement, fostering public trust and facilitating widespread adoption of future wireless technologies.

5. Conclusion

This paper presented a quantitative overview of the intertwined requirements imposed by the co-evolution of AI and 6G, which are driven by the scenarios where AI enhances the design and operation of future networks, while 6G infrastructure must support the computational and operational demands of emerging AI paradigms. Through the emergence of essential use-cases, such as AI training and inference as a service, and LLM-based orchestration, we demonstrated how 6G must evolve into an AI-native platform for supporting dynamic resource allocation, intelligent data management, and programmable services, among others. On the other hand, we outlined how AI impacts 6G performance requirements over latency, bandwidth, energy efficiency, scalability, trust, to name a few. By measuring these mutual requirements, this paper offers a foundation for guiding standardization and system/network-level design, ensuring that future networks are not just optimized by AI, but they are AI-enabling platforms at their core.

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Design and Analysis of Millimeter-wave Antenna for New Radio (NR) 5G Bands Supporting a Green Wireless Future

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Abstract: Millimeter-wave (mmWave) fifth-generation (5G) networks play a pivotal role in advancing point-to-point communication and connectivity by leveraging cutting-edge 5G technology. These networks enable high-speed data transfer, low latency, and reliable wireless communication, making them essential for a wide range of 5G applications and services, while contributing to a green wireless future through efficient and sustainable designs. The proposed mmWave Multiple-Input-Multiple-Output (MIMO) antenna is a compact and lightweight solution specifically designed for seamless integration into 5G networks and other mmWave devices. Operating across a wide frequency range of 24–34 GHz, it offers an impressive impedance bandwidth of 10 GHz, effectively covering key New Radio (NR) 5G bands, including n257 (26.50–29.50 GHz), n258 (24.25–27.50 GHz), and n261 (27.50–28.35 GHz). With dimensions of just 25 × 10 mm^2, the antenna is fabricated on an RO4350B substrate with a thickness of 0.51 mm, ensuring a compact footprint suitable for modern applications. It delivers exceptional performance, achieving a peak efficiency of over 94% and gains of 5.35 dBi at 26 GHz, 6.4 dBi at 28 GHz, and 5.0 dBi at 32 GHz. The fabricated prototype closely matches simulation results, demonstrating its suitability for NR 5G frequency bands while aligning with the goals of a green wireless future. By enhancing energy efficiency, minimizing material usage in fabrication and reducing network power consumption, this research directly contributes to the development of a sustainable 5G ecosystem, supporting global efforts to achieve environmentally responsible wireless technologies.

Keywords: Millimeter-wave antenna, new radio 5G band, n257, n258, n261, energy efficiency, and sustainability.

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1. Introduction

Millimeter-wave (mmWave) antennas are integral to achieving the high data rates and ultra-low latency required for 5G applications. Operating at frequencies above 24 GHz, they offer substantial bandwidth, enabling the seamless transmission of large data volumes. Due to the shorter wavelengths at mmWave frequencies, advanced antenna arrays and beamforming techniques are crucial for mitigating propagation challenges and ensuring reliable connectivity in dense urban 5G environments [1]. As a key enabler of 5G networks, mmWave antennas provide significantly greater bandwidth capacity than traditional cellular frequencies, making them ideal for high-demand applications such as virtual reality (VR), augmented reality (AR), autonomous vehicles, and the Internet of Things (IoT) [2]. Globally, 123 operators across 42 countries, including the USA, Europe, South Korea, Japan, and China, are actively investing in 5G technologies through trials, licensing, deployments, and operational networks. These efforts primarily target the 24.25–29.5 GHz spectrum, a crucial band for 5G service development. The n257 band (26.5–29.5 GHz), extensively utilized in Japan, North America, and South Korea, has been rigorously tested and plays a pivotal role in the 5G mmWave spectrum, serving as a capacity layer for short-range, high-speed transmissions. In Europe and China, the n258 band (24.25–27.5 GHz) is a key mmWave allocation that has undergone significant testing for widespread adoption. At the upper end of the spectrum, the n261 band (28 GHz), spanning 27.5–28.35 GHz, is the highest frequency band in the 5G ecosystem. It is often deployed alongside the n260 band (39 GHz) to enhance short-range, high-data-rate transmissions, which are fundamental to mmWave technology [3].

2. Related Work

The mmWave antennas in 5G applications are developed using methodologies like microstrip-fed slot, defected ground structure (DGS), electromagnetic band gap (EBG), and substrate-integrated waveguide (SIW) techniques. Choosing a design approach depends on the application's particular needs and comes with its unique set of advantages and drawbacks like antenna size, efficiency, beam steering capabilities, and impedance bandwidth. The authors in [4] propose a four-element linear array mmWave 5G cellular antenna operating in the 28 GHz band. The antenna features a vertically stacked configuration, utilizing a multilayer printed circuit board (PCB) via holes to enhance bandwidth and efficiency. However, including the spacers (i.e. via holes) add complexity to the design and testing process. The operating frequency of the linear array is 26.3 to 29.75 GHz, with a narrow impedance bandwidth of 3.72 GHz, which is unsuitable for practical 5G mmWave applications. The authors in [5] presented a broadband four-element mmWave antenna designed for 5G mmWave applications. The antenna operates within the frequency range of 23–30.5 GHz, with a total antenna size of 26 $\times$ 5 $\times$ 1.524 mm^3. Furthermore, to enhance impedance matching (for broad bandwidth) and isolation levels, four sets of 2 $\times$ 3 parasitic square array patches are integrated into the proposed 1 $\times$ 4 antenna array. However, the total efficiency exceeds 68%, making it unsuitable for practical 5G devices like smartphones.

The authors in [6] designed a mmWave four-element Vivaldi antenna array for 5G communication, operating across LTE low band (700–960 MHz, 1710–2690 MHz) and high band (25–30 GHz). The antenna exhibits broad performance capabilities, featuring an impedance bandwidth of 5 GHz and achieving a total efficiency exceeding 60%, which is relatively low for practical mmWave devices. An eight-element mmWave phased array antenna, designed for 28 GHz 5G applications, incorporates two sets of 1 $\times$ 8 back-cavity slot arrays positioned along the longer side edges of the metal cover to facilitate beam steering [7]. Operating within the 27.5–30 GHz frequency range, the antenna supports high-gain directional transmission. However, its limited impedance bandwidth of 2.5 GHz restricts its adaptability for practical mmWave 5G applications, where broader bandwidth is essential for enhanced data throughput and seamless connectivity. A substrate-integrated waveguide (SIW)-based mmWave antenna, developed for 5G mmWave applications, integrates two semi-circle patches and two suspended metal posts to enhance performance [8]. Operating within the 20.7–29.8 GHz frequency range, it achieves an impressive 9.1 GHz impedance bandwidth, ensuring broad-spectrum coverage. However, the intricate design and complex testing process present significant challenges, limiting its practicality for real-world 5G communication devices, where scalability, manufacturability, and ease of integration are critical.

The author in [9] designed the mmWave antenna to resonate specifically at 37.5 GHz, operating within the frequency range of 36.6-38.9 GHz with an impedance bandwidth of 2.3 GHz. However, the results of the fabricated model are not discussed, which does not validate the antenna performance for practical devices. The authors in [10] designed and developed a mmWave antenna operating at 28 GHz with an impedance bandwidth of 1.7 GHz, featuring a gain of 3.86 dBi and a total efficiency of 83%. However, the antenna's gain is low, and its bandwidth is very narrow, making it unsuitable for practical 5G devices.

The proposed mmWave MIMO antenna provides a compact, high-performance solution for 5G networks, with a wide frequency range (24–34 GHz), high efficiency (>94%), high gains (5.0–6.4 dBi), and precise support for NR 5G bands, ensuring seamless integration into advanced communication systems.

3. MIMO Antenna Configuration

This research presents a compact, light-weight, wideband mmWave MIMO antenna designed for NR 5G bands, with overall dimensions of 25×10×0.51 mm^3. The antenna possesses a simple structure that can be easily fabricated, tested, and integrated with mmWave devices. It is designed and simulated using Computer Simulation Technology (CST) 2022 using RO4350B substrate with a thickness of 0.5 mm. The proposed antenna incorporates two innovative techniques to enhance its performance. The Defective Patch Structure Technique (DPST), referred to as the front view and shown in Figure 1, significantly improves the antenna's gain and efficiency, making it essential for long-range communication and addressing signal attenuation challenges at higher frequencies. Additionally, the Defective Ground Structure Technique (DGST), referred to as the back view and illustrated in Figure 2, enables wideband operation, which is crucial for supporting high data rate applications in mmWave communication systems.

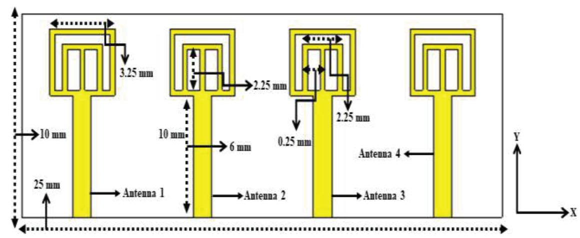

Figure 1.

Front view (defective patch structure technique) of four element MIMO antenna.

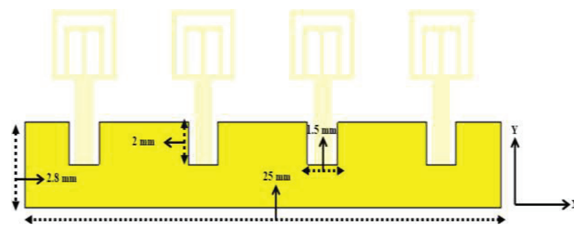

Figure 2.

Back view (defective ground structure technique) of four element MIMO antenna.

4. Results and Discussions

The proposed MIMO antenna operates within the 24–34 GHz frequency band with an impedance bandwidth of 10 GHz. Additionally, the antenna covers the three NR 5G bands of n257, n258, and n261. The simulated response of the MIMO antenna, depicted in Figure 3, is suitable for future 5G networks. The port isolation of the four-element MIMO system, as shown in Figure 4, indicates an isolation of 21.1 dBi at 26 GHz and 32.5 dBi at 32 GHz.

The MIMO antenna demonstrates good performance characteristics like gain, radiated efficiency, and total efficiency as shown in Figure 5. At 26 GHz, the antenna exhibits a gain of 5.35 dBi with a radiated efficiency of 96% and a total efficiency of 91%. Similarly, at 28 GHz, the antenna shows an increase of 6.4 dBi with a radiated efficiency of 95.85% and a total efficiency of 92.5%. Additionally, at 32 GHz, the antenna displays a gain of 5 dBi with a radiated efficiency of 95.45% and a total efficiency of 90.89%,

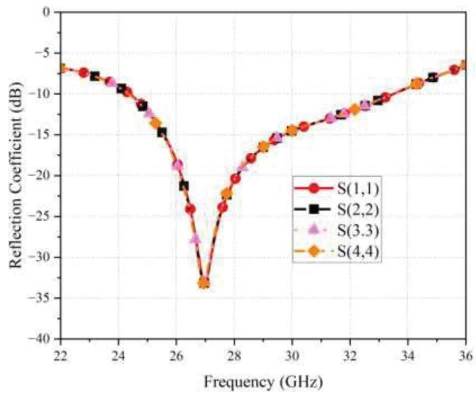

Figure 3.
Reflection co-efficient of the proposed MIMO antenna.

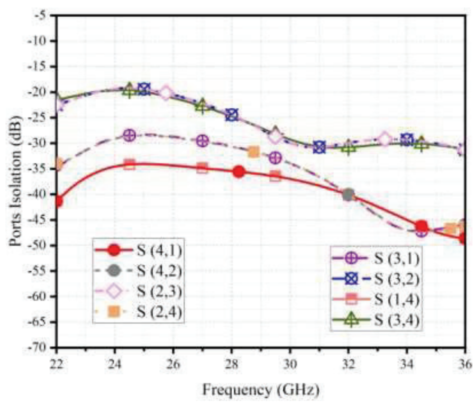

Figure 4.
Ports isolation of the proposed MIMO antenna.

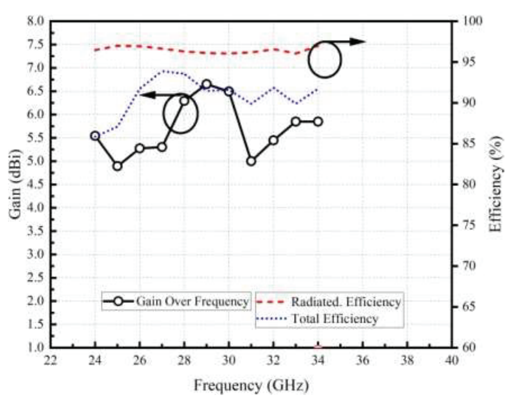

Figure 5.
Gain, radiated and total efficiency of the proposed MIMO antenna.

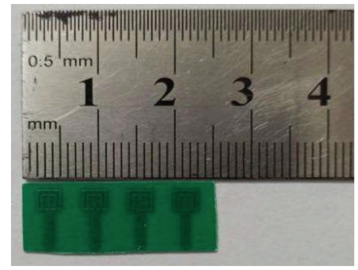

Figure 6.
Fabricated prototype of the proposed MIMO antenna.

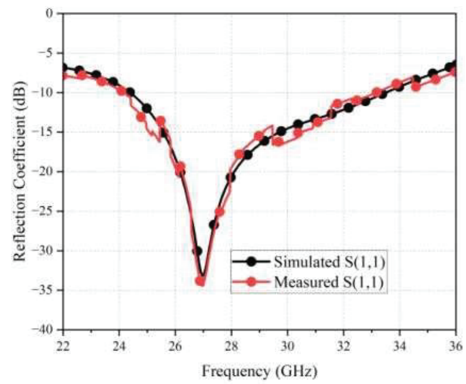

Figure 7.
S11 simulated and measured reflection co-efficient.

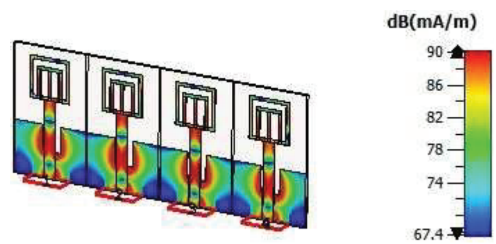

Figure 8.
Surface current of MIMO antenna at 28 GHz.

making it suitable for NR 5G bands. The Figure 6 illustrates the fabricated prototype of four element MIMO antenna.

Figure 7 shows the simulated and measured reflection coefficient responses of the proposed four-element MIMO system. The solid black line represents the simulated data, while the solid red line represents the measured data. This illustrates a strong correlation between the simulated and measured results, suitable for sustainable 5G networks.

The surface current at 28 GHz is illustrated in Figure 8, and it is noted that the surface current is enhanced due to DPST and DGST techniques. The current direction is primarily focused on the outer edges and the ground slot, circulating strong current among the radiating elements. Furthermore, the 3D gain at 28 GHz is shown in Figure 9, depicting the antenna radiation in a three-dimensional view.

The radiation patterns at 28 GHz for two planes, Phi (0) and Phi (90), are illustrated in Figures 10 and 11. The Phi (0) plane represents the zx axis of the antenna, with the main lobe direction at 0° and a 3 dB angular width of 83.5°. The Phi (90) plane represents the xy axis of the antenna, with the main lobe slightly tilted to 356° and a side lobe level of −1.2 dB, showcasing their

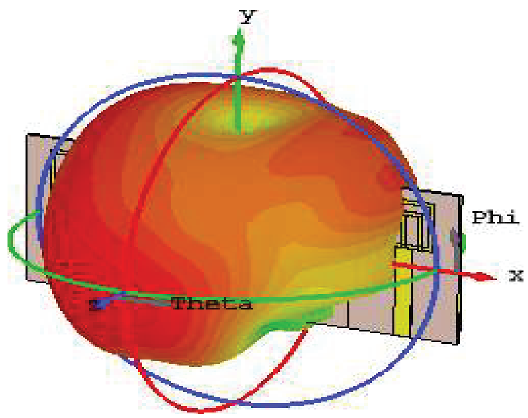

Figure 9.
3D gain of MIMO antenna at 28 GHz.

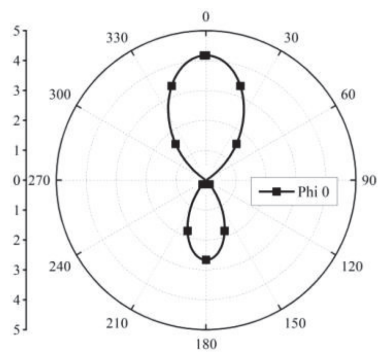

Figure 10.
Radiation pattern phi (0) at 28 GHz.

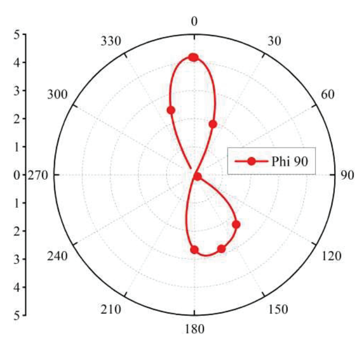

Figure 11.
Radiation pattern phi (90) at 28 GHz.

potential for practical NR 5G bands that promote a sustainable wireless future.

The proposed mmWave MIMO antenna design supports a wide bandwidth of 10 GHz (24–34 GHz), enabling high data throughput essential for 5G FR2 performance. Based on the Shannon–Hartley theorem and real-world system modeling, the spectral efficiency is estimated using the following relation:

$$\eta_{\text{spectral}} = \log_2(1 + \text{SNR}) \times N_{\text{streams}} \text{ (bps/Hz)}$$

For a Line-of-Sight (LOS) condition in a Single-User MIMO (SU-MIMO) scenario with 4×4 MIMO configuration and a moderate SNR of 15 dB, the achievable spectral efficiency is:

$$\eta_{\text{LOS}}^{\text{SUMIMO}} = \log_2(1 + 31.6) \times 4 \approx 5 \times 4 = 20 \text{ bps/Hz}$$

For Non-Line-of-Sight (NLOS) conditions under Multi-User MIMO (MU-MIMO) using beamforming, assuming an effective SNR of 10 dB and 2 parallel streams per user:

$$\eta_{\text{NLOS}}^{\text{MU-MIMO}} = \log_2(1 + 10) \times 2 \approx 3.46 \times 2$$
$$= 6.92 \text{ bps/Hz per user}$$

Therefore, the proposed antenna supports spectral efficiency values ranging from 6.9 to 20 bps/Hz, depending on the propagation scenario and MIMO mode. These performance metrics align with the typical requirements for 5G NR FR2 communication systems and validate the suitability of the proposed design for high-capacity mmWave deployments.

Most substrates (like RO4350B) have a temperature-dependent dielectric constant. This dependence is expressed as:

$$\epsilon_r(T) = \epsilon_{r0} + \partial_\epsilon \times (T - T_0)$$

Where:

- $\epsilon_r(T)$: Dielectric constant at temperature T(°C)
- ϵ_{r0}: Dielectric constant at reference temperature T_0 (typically 25°C)
- ∂_ϵ: Temperature coefficient of dielectric constant (ppm/°C or parts per million per °C)

For RO4350B, $\partial_\epsilon \approx 50$ ppm/°C, or:

$$\partial_\epsilon = 50 \times 10^{-6}$$

The resonant frequency f_r of a microstrip antenna is inversely proportional to the square root of the dielectric constant:

$$f_r \propto \frac{1}{\sqrt{\epsilon_r}}$$

So, an increase in ϵ_r due to temperature causes a decrease in resonant frequency:

$$\Delta f_r \approx -\frac{1}{2} f_r \times \frac{\Delta \epsilon_r}{\epsilon_r}$$

Where:

$$\Delta \epsilon_r = \partial_\epsilon \times (T - T_0) \cdot \epsilon_{r0}$$

For example, if:

$$\epsilon_{r0} = 3.48$$
$$\partial_\epsilon = 50 \times 10^{-6}$$
$$T - T_0 = 60°\text{C}$$

Then:

$$\Delta \epsilon_r = 3.48 \times 50 \times 10^{-6} \cdot 60 \approx 0.0104$$

And the fractional frequency shift:

$$\frac{\Delta f_r}{f_r} \approx -\frac{1}{2} \times \frac{0.0104}{3.48} \approx -0.00149 \Rightarrow -0.149\%$$

So, for a center frequency of 28 GHz:

$$\Delta f_r \approx -0.149\% \times 28 \text{ GHz} \approx -41.7 \text{ MHz}$$

This is negligible in a wideband system (10 GHz bandwidth), proving thermal resilience. The antenna gain G is affected by mismatch due to ϵ_r variation. Mathematically:

$$G = \eta_e \cdot D$$

Where:

η_e: Radiation efficiency (can drop due to mismatch or added loss)
D: Directivity

Assuming small ϵ_r variation leads to mismatch (in return loss or VSWR), we estimate the gain drop as:

$$\Delta G \approx \frac{\partial G}{\partial \epsilon_r} \cdot \Delta \epsilon_r$$

Let's assume:

$$\frac{\partial G}{\partial \epsilon_r} \approx 0.2 \text{ dBi/unit}$$

Then:

$$\Delta G \approx 0.2 \cdot 0.0104 \approx 0.00208 \text{ dBi}$$

0.00208 dBi is extremely small value, which implies that even under thermal drift, the gain performance is stable.

5. Conclusion

The proposed mmWave MIMO antenna is compact and lightweight, operates across a broad frequency range of 24–34 GHz, with an impressive impedance bandwidth of 10 GHz. It covers essential NR 5G bands like n257, n258, and n261, contributing to a green wireless future by promoting efficient and sustainable communication technologies. With dimensions of 25×10 mm^2 and boasting exceptional performance characteristics such as a peak efficiency exceeding 94% and gains of 5.35 dBi at 26 GHz, 6.4 dBi at 28 GHz, and 5.0 dBi at 32 GHz. The proposed antenna demonstrates strong alignment with simulation results, confirming its suitability for NR 5G frequency bands. The antenna's design and fabrication process, incorporating the DPST and the DGST, ensures enhanced gain, efficiency, and wideband operation critical for optimizing communication over long distances and at higher frequencies. This research highlights the significance of the compact, wideband mmWave MIMO antenna in driving the evolution and efficiency of NR 5G networks, while aligning with the vision of a green wireless future.

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SDN-Enabled Energy-Aware Routing and Distribution for Circular Sustainable Industrial Ecosystems: A Dynamic Optimization Approach

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Abstract: The transition to circular sustainable industrial ecosystems necessitates innovative energy management solutions that balance environmental responsibility, efficiency, and social adaptability. This research introduces a Software-Defined Networks (SDN) enabled framework that integrates energy-aware optimization techniques to achieve real-time, dynamic energy management. The proposed system addresses key challenges in circular sustainable business models (CSBMs), such as optimizing energy distribution, minimizing waste, and integrating renewable energy sources, thereby supporting the transition to a circular economy. Industrial ecosystems often suffer from inefficient energy management, leading to high operational costs, increased carbon emissions, and poor resource utilization. To overcome these challenges, this research proposes an intelligent and dynamic energy management framework that leverages SDN's centralized control and energy-aware routing algorithms to optimize energy flow in real time. This ensures efficient energy utilization, reducing both waste and costs while enhancing sustainability. The framework incorporates an energy-aware routing algorithm that prioritizes energy-efficient paths based on power consumption, latency, and carbon footprint. It integrates an SDN controller with Industrial Internet of Things (IIoT) sensors, which monitor energy consumption, environmental conditions, and renewable energy availability. This real-time data enables the system to dynamically adjust energy distribution, ensuring that energy supply meets demand efficiently. A key contribution of this research is the integration of renewable energy sources (e.g., solar panels) and energy storage systems (e.g., batteries) into industrial networks. This enhances sustainability by reducing dependence on non-renewable energy and lowering the carbon footprint. The framework is designed to be scalable and flexible, accommodating new energy sources, storage units, and production demands as industrial ecosystems expand. This research contributes to circular sustainable business models by enabling smarter, greener, and more resilient industrial energy management, aligning with Triple Bottom Line (TBL) principles to promote economic, environmental, and social sustainability.

Keywords: Circular sustainable business models (CSBMs), renewable energy, software defined networks (SDN).

1. Introduction

The increasing demand for sustainable industrial practices has driven a paradigm shift toward circular industrial ecosystems, where energy efficiency and resource optimization are critical [1]. Traditional industrial energy management systems often exhibit inefficiencies due to rigid architectures, limited dynamic energy distribution capabilities, and poor integration with renewable energy sources [2]. These shortcomings lead to higher operational costs, excessive energy waste, and increased carbon emissions, impeding progress toward a circular economy [3]. The push for sustainability and digital transformation has accelerated the adoption of advanced technologies enabling real-time, intelligent energy management [4]. By leveraging SDN and the IIoT, industries can improve energy efficiency, optimize distribution, and seamlessly integrate renewables [5].

SDN is a transformative technology that offers centralized control, programmability, and dynamic resource allocation, making it ideal for industrial energy optimization [6]. Unlike conventional energy networks with static configurations, SDN enables adaptive routing based on real-time demand, consumption patterns, and environmental factors [7]. When combined with energy-aware routing algorithms, SDN minimizes power losses and enhances sustainability in industrial ecosystems. Similarly, IIoT provides critical real-time data on energy consumption, production, and renewable generation, enabling smarter decision-making [5]. The integration of SDN and IIoT facilitates an intelligent energy management system that continuously optimizes energy flows, reducing costs and environmental impact.

Despite SDN's potential, most research focuses on network optimization rather than holistic energy management in industrial settings. Existing approaches often lack adaptability to fluctuating energy demands and struggle with renewable integration [3]. Additionally, challenges such as computational complexity, data accuracy, and cybersecurity risks remain understudied. This research addresses these gaps by developing a dynamic SDN-enabled optimization framework for real-time energy distribution. By overcoming these limitations, the proposed system enhances efficiency,

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reduces carbon emissions, and supports circular economy principles through cross-sectoral business models (CSBMs) [3].

The primary objective of this study is to design a scalable, SDN-driven energy management system that optimizes industrial energy distribution. The framework incorporates energy-aware routing, integrates solar and battery storage systems, and dynamically adjusts flows using IIoT data. Additionally, the research investigates computational overhead and security risks while proposing mitigation strategies to improve system reliability and scalability.

2. Related Work

Circular Sustainable Industrial Ecosystems (CSIEs) are emerging as a pivotal framework in advancing sustainable industrial practices by promoting resource efficiency and waste minimization. This approach emphasizes the transformation of traditional linear production models into circular systems where waste is repurposed as input for other processes, thereby fostering environmental sustainability and economic resilience. Recent studies have highlighted the integration of circular economy principles within manufacturing sectors, identifying significant barriers such as economic, technological, and regulatory challenges, while also showcasing innovative strategies and business models that successfully apply circular principles [8].

The development and implementation of multi-business models within these symbiotic networks are considered critical for the successful realization of CSIEs. The concept of Green Multi Business Models has been extensively explored in paper [9], with a focus placed on the measurement and innovation of green business practices. The importance of designing business models that create, capture, deliver, receive, and consume value in alignment with sustainability goals is emphasized in his research. The complexity of balancing monetary and non-monetary value within business models, particularly in symbiotic networks involving multiple stakeholders, is highlighted by the authors. This balance is regarded as essential to ensure that green business models are genuinely sustainable rather than merely superficial adaptations [9].

In the context of industrial symbiosis, the efficient exchange of resources, energy, and information is facilitated through the collaboration between different enterprises. The significance of understanding the coherence between individual business models and the larger ecosystem in which they operate is underscored in one of the author's works on business model ecosystems. This perspective is regarded as vital for the fostering of innovation and resilience within industrial symbiotic networks, as it allows for the strategic alignment of diverse business models towards common sustainability objectives [10–12].

The implementation of CSIEs necessitates robust and adaptable network infrastructures capable of managing complex and dynamic industrial processes. The integration of advanced technologies, such as SDN, into these ecosystems can further enhance their efficiency and adaptability. SDN offers centralized control and programmability of network resources, enabling dynamic optimization of data flows and energy consumption. This technological synergy supports the real-time monitoring and adaptive management of complex industrial processes, thereby reinforcing the sustainability and operational efficiency of CSIEs. Studies have demonstrated that SDN-based energy-aware routing protocols can optimize power consumption in Wireless Sensor Networks (WSNs) within the IIoT framework, supporting Industry 4.0 initiatives [13].

Further research has explored the application of SDN in multi-hop wireless sensor networks, proposing energy-aware routing algorithms and control overhead reduction techniques to prolong network lifetime. These approaches leverage SDN's centralized control to optimize energy consumption, which is critical for the sustainability of IIoT services [14].

The convergence of SDN technology with CSIEs offers a promising avenue for achieving dynamic optimization in industrial processes. By enabling real-time monitoring and adaptive control of network resources, SDN facilitates the seamless integration of various industrial components, promoting sustainability and operational efficiency. This dynamic optimization approach addresses the energy demands of industrial networks and aligns with the overarching goals of circular economy principles, fostering resilient and sustainable industrial ecosystems [15].

3. System Model

The proposed system model integrates SDN with an Energy-Aware Algorithm to optimize energy distribution in circular sustainable industrial ecosystems. The model leverages SDN's centralized control capabilities to dynamically manage energy flows while ensuring alignment with CSBMs. By incorporating real-time data collection, renewable energy prioritization, and energy-aware optimization techniques, this system enhances energy efficiency, reduces waste, and contributes to environmental and economic sustainability. The Energy-Aware Algorithm, a core component of the system, is designed to select the most energy-efficient paths within an industrial network by considering factors such as power consumption, latency, and the availability of renewable energy sources.

In conventional industrial networks, shortest path algorithms are commonly used to determine the shortest path based on metrics like distance or latency. However, this approach does not account for energy consumption or sustainability. The modified Energy-Aware Algorithm redefines the path selection process by incorporating energy-related metrics, ensuring that energy is distributed through the most sustainable and circular pathways. The algorithm assigns weights to network edges based on power usage, energy efficiency, carbon footprint, and renewable energy availability. This weighted graph representation allows the system to prioritize routes that minimize energy waste while maximizing the utilization of sustainable energy sources.

The industrial network is modeled as a graph (shown in Figure 1) where nodes represent industrial devices, renewable energy sources, and energy distribution points, while edges signify energy distribution and communication links. Each edge in the graph is assigned a weight based on its energy consumption and sustainability metrics. A priority queue mechanism ensures that the algorithm selects the most energy-efficient path first, improving network adaptability and scalability. The Energy-Aware Algorithm operates in a stepwise manner, beginning with the initialization of tentative energy costs for all nodes, followed by iterative path exploration based on energy-aware metrics. Nodes are marked as visited once analyzed, preventing redundant computations and

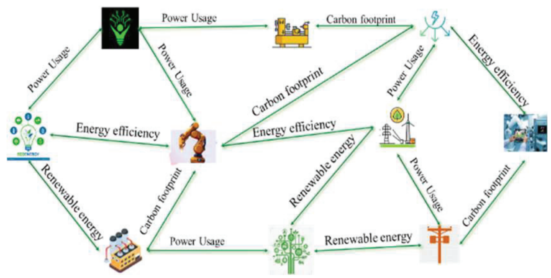

Figure 1.
Modeled industrial network.

enhancing efficiency. The algorithm then reconstructs the most sustainable path, ensuring optimal energy distribution in real time.

One of the key advantages of integrating SDN with energy-aware routing is the system's real-time adaptability. The SDN controller continuously collects data from IIoT sensors deployed across the industrial ecosystem. These sensors monitor various parameters, including energy consumption, production rates, and environmental conditions. Based on this data, the SDN controller dynamically adjusts energy flows, ensuring that energy supply aligns with real-time demand while prioritizing sustainability. The system seamlessly integrates renewable energy sources, such as solar panels and battery storage systems, to reduce reliance on non-renewable energy and lower the overall carbon footprint of industrial operations.

The proposed system model offers several advantages, including enhanced energy efficiency, circularity, flexibility, and scalability. By prioritizing energy-efficient paths, it minimizes operational costs and ensures that energy is distributed in a sustainable manner. The circular economy principles embedded within the model promote resource efficiency and closed-loop energy management, reducing waste and optimizing renewable energy use. Furthermore, the model is designed to accommodate future industrial expansion, allowing for the seamless integration of additional production units, energy sources, and storage systems. The combination of SDN, energy-aware routing, and renewable energy integration provides an intelligent and adaptive solution for real-time dynamic energy management in circular industrial ecosystems, paving the way for smarter, greener, and more sustainable industrial practices.

4. Working of Proposed Framework

The proposed system formalizes the optimization of energy distribution using SDN and Energy-Aware Algorithm. The model aims to minimize energy waste, maximize renewable energy utilization, and ensure an efficient, sustainable energy flow in industrial ecosystems.

The Algorithm shown below (Algorithm 1) in industrial network is represented as a weighted graph (as shown in Figure 2), where nodes correspond to industrial devices, renewable energy sources, and distribution points, while edges represent energy distribution links between these nodes. The edge weights are determined based on real-time energy consumption data, with lower weights assigned to paths that have lower energy costs and higher renewable energy contributions. The SDN controller continuously collects data from IIoT sensors deployed across the industrial ecosystem, enabling real-time adjustments to energy routing decisions based on dynamic demand and supply conditions.

The algorithm begins with an initialization step, where all nodes are assigned a tentative energy cost of infinity, except for the source node, which is set to zero. A priority queue is used to select the node with the lowest tentative energy cost, ensuring that the most energy-efficient paths are explored first. The algorithm iteratively examines neighboring nodes, updating their energy costs based on metrics such as energy efficiency, latency, and renewable energy utilization. If a more efficient path is found, the tentative cost is updated, and the process continues until all nodes are visited or the most energy-optimal path is identified. The final step involves reconstructing the optimal path from the destination back to the source, ensuring that energy is distributed through the most sustainable and cost-effective routes.

1. Initialize:
a. Set energy cost of all nodes to ∞ Set source node S=0
b. Create an empty priority queue Q.
c. Add source node S to Q.

2. While Q is not empty:
a. Extract the node U from Q with the lowest energy cost.
b. Mark U as visited.

3. For each unvisited neighbor V of U:
a. Calculate tentative energy cost:
Cost(V) = Cost(U) + w(U, V),
where w(U, V) is cumulative edge weights of parameters

b. If Cost(V) < previous Cost(V), update:
- Set Cost(V) to the newly calculated cost.
- Set U as the predecessor of V.
- Update V in Q with Cost(V).

4. If Destination node D is reached, construct the optimal path by tracing predecessors.

5. Output the optimal energy-aware path from S to D with the lowest energy cost.

Algorithm 1.
Energy aware routing algorithm.

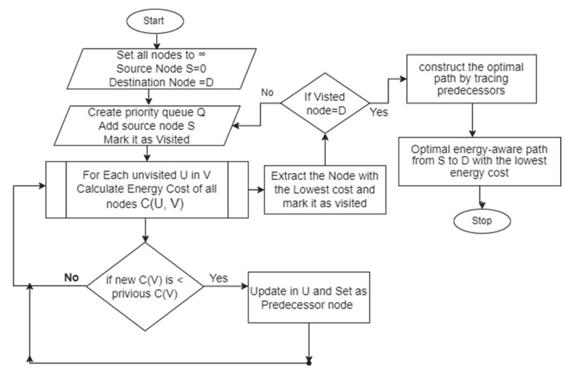

Figure 2.
Flow chart of the proposed framework.

A key advantage of this algorithm is its real-time adaptability when integrated with SDN. The SDN controller dynamically adjusts energy flow paths based on fluctuating energy demand, renewable energy availability, and operational constraints. This scalability and flexibility make it particularly effective for smart factories and industrial ecosystems, where energy demands frequently change due to varying production loads and external conditions. And by prioritizing paths that maximize renewable energy use, the framework significantly reduces dependence on non-renewable energy sources, thereby lowering carbon emissions and operational costs.

The Energy-Aware Algorithm offers a scalable, intelligent, and sustainable solution for real-time energy optimization in industrial settings. By combining SDN-driven centralized control with circular sustainability principles, it ensures optimal energy efficiency, reduces waste, and supports the transition toward a circular economy. This approach paves the way for greener, more resilient industrial operations, shaping the future of sustainable energy management in industrial ecosystems.

5. Results and Discussion

The proposed SDN-enabled energy-aware routing framework demonstrates significant improvements in energy management for circular sustainable industrial ecosystems. By integrating SDN with an Energy-Aware Algorithm, the system dynamically optimizes energy distribution, ensuring efficient utilization of available energy resources while minimizing waste. This approach enables real-time decision-making based on factors such as power consumption, latency, energy efficiency, and renewable energy availability, making industrial energy networks more sustainable and resilient.

One of the key outcomes of this framework is the optimization of energy flow through intelligent routing. Unlike traditional energy management systems that operate on static configurations, this approach continuously adjusts energy paths based on real-time data collected from IIoT sensors. The integration of real-time monitoring and SDN control allows for dynamic adaptation to fluctuating energy demands, preventing inefficiencies caused by over- or under-utilization of resources. This adaptability is crucial in industrial environments, where energy consumption varies based on production loads, external conditions, and operational constraints.

Another major benefit of this approach is the prioritization of renewable energy sources in the energy routing process. By incorporating renewable energy availability into the path selection algorithm, the system ensures maximum utilization of solar, wind, and energy storage systems, thereby reducing reliance on non-renewable energy sources. This directly contributes to lower carbon emissions, supports environmental sustainability, and aligns with circular economy principles by promoting efficient resource utilization.

The proposed framework also enhances energy efficiency by selecting the most energy-optimal paths, reducing overall power consumption and operational costs. Traditional routing methods often prioritize shortest-distance paths, which may not necessarily be the most energy-efficient. In contrast, the Energy-Aware Algorithm evaluates multiple sustainability-related metrics, ensuring that the selected paths minimize energy losses and improve network-wide efficiency.

The proposed SDN-enabled energy-aware routing framework offers a scalable and sustainable solution for real-time energy management in circular industrial ecosystems. By integrating centralized control, real-time monitoring, and energy-aware optimization, the system significantly enhances energy efficiency, reduces waste, and promotes the use of renewable energy sources. This approach plays a critical role in advancing CSBMs, ensuring that industrial operations remain economically viable, environmentally responsible, and socially sustainable.

6. Conclusion

The proposed SDN-enabled energy-aware routing framework presents a dynamic and efficient solution for real-time energy management in circular sustainable industrial ecosystems by integrating SDN and an Energy-Aware Algorithm. This approach optimizes energy distribution by prioritizing power efficiency, renewable energy utilization, and sustainability, reducing waste and minimizing carbon emissions while ensuring adaptability to fluctuating energy demands. The integration of real-time monitoring through IIoT sensors and centralized SDN control enhances flexibility, making industrial energy networks more resilient and efficient. Although challenges such as computational complexity, data accuracy, and cybersecurity risks remain, addressing these aspects will further strengthen the framework's scalability and reliability. This research contributes to advancing CSBMs by enabling smarter, greener, and more sustainable industrial energy management that aligns with the principles of the circular economy and the TBL approach.

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Biographies

Shivaleela Arlimatti is accomplished individual in the field of Computer Science and Engineering. She is the director of Sathodi Technologies private limited. She completed her PhD at the University Utara Malaysia, Malaysia, and holds a Master of Technology degree from the University of Mysore, Mysore. Currently, she serves as a Professor and the Head of the Department at Tatyasaheb Kore Institute of Engineering & Technology, Warana University Warananagar, Kolhapur, Maharashtra, India. With a remarkable teaching career spanning 20 years, Shivaleela has made significant contributions to the academic community. Her expertise and dedication are evident in her extensive research work. She has published 25+ research papers in both national and international journals and conferences, showcasing her commitment to advancing knowledge in her field. She has contributed to the academic literature through book chapters. She has two patents and one copyright published on her name.

Arlimatti's professional affiliations include being a life member of the Indian Society for Technical Education (ISTE) and the Indian chapter of the Internet Society (ISOC). She is also a member of the Malaysian chapter of ISOC, further highlighting her international connections and collaborations. Through her research, teaching, and active involvement in professional organizations, Shivaleela Arlimatti continues to make valuable contributions to the field of Computer Science and Engineering, inspiring and guiding future generations of students and researchers.

Rajesh Gade holds a Master of Engineering in Computer Science and Engineering and a Bachelor of Engineering in Information Technology. With extensive experience in the technology and business sectors, Rajesh has worked with leading companies such as Infosys, Wipro, and Juniper Networks. A practitioner of Multi-Business Model Innovation and the Business Model Canvas, he has been instrumental in helping organizations develop innovative business strategies. Rajesh served as the Chief Operating Officer (COO) for KITE – KIT's Incubation for Technology Entrepreneurship, where he played a key role in fostering technological innovation and entrepreneurship. In addition to his work in technology and academia, Rajesh has hands-on experience in cashew manufacturing and jaggery trading and exports, further expanding his business expertise across diverse sectors. Rajesh was also a Task Manager for the European Union's ERASMUS+ project CENTRAL, where he contributed to the development and management of the project across several countries, including Denmark, Thailand, Malaysia, and other parts of Europe. This international exposure allowed him to work on significant cross-border initiatives, fostering collaboration between academic and industry stakeholders globally. Currently, Rajesh serves as an Assistant Professor and Central Learning Management Head at Warana University, where he is focused on advancing education and learning management. He is also the Founder and Director of Crystal Clear Imports and Exports and Founder Director of INNOeVERSITY, focusing on global business development and innovation. Rajesh is passionate about mentoring aspiring entrepreneurs and professionals, helping them navigate the complexities of business development, international trade, and global collaborative projects.

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Suresh D. Mane is a distinguished academic and engineering professional with a strong educational background, holding a Ph.D. in Industrial & Production Engineering from Kuvempu University (2015), an M.Tech. in Energy Systems Engineering from BVB College of Engineering (VTU, 2007), and a B.E. in Mechanical Engineering from Karnatak University (1991). His doctoral research focused on energy performance and environmental sustainability in Indian Railway workshops, resulting in ten peer-reviewed international publications. With over 32 years of experience – 20 in South Western Railways and 12+ in academia. Mane has held key leadership roles, including Principal at Dr. D Y Patil College of Engineering (2022–present) and Girijabai Sail Institute of Technology (2015–2022), where he drove institutional growth through NAAC/NBA accreditation, faculty development, and infrastructure modernization. His earlier roles include senior engineering positions in Railways, earning him 12 meritorious service awards.

Mane's research spans energy conservation, biodiesel applications, thermal engineering, accreditation, Outcome-Based Education (OBE), and sustainable education. He has guided three Ph.D. candidates, published 57 Scopus/SCI-indexed papers, and contributed chapters to Springer publications. Notable projects include biofuel applications in engines and energy audits in railway workshops. A dynamic leader, he has spearheaded NAAC accreditation, established advanced research labs, organized 20+ conferences, and conducted 30+ faculty development programs. Recognized for his contributions, he holds an impressive API score of 777 under UGC's PBAS Category III and serves as an editorial reviewer for leading journals.

A Fellow of the Institution of Engineers (India) and a Certified Energy Manager (BEE), Mane has received multiple accolades, including the Best Principal of the Year (2023) and the Education Excellence Award (2024). His blend of administrative expertise and research innovation continues to advance higher education and sustainable engineering practices.

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Edge-Optimized Cloud Detection and Segmentation Using ResNet

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Abstract: Accurate cloud detection and segmentation in satellite imagery are critical for applications such as weather forecasting, environmental monitoring, and disaster management. Traditional methods often struggle with the variability and complexity of cloud formations, leading to limitations in accuracy and efficiency. This project addresses these challenges by leveraging deep learning techniques, specifically the ResNet-50 architecture integrated with U-Net, to enhance the precision and robustness of cloud detection. The model is trained on the 38-Cloud dataset, which includes multi-spectral satellite images with pixel-level annotations, enabling effective differentiation between cloud types and other atmospheric features. The proposed system emphasizes deployment on edge devices, such as NVIDIA Jetson Nano, to facilitate real-time processing and analysis directly within satellites, reducing latency and enabling continuous monitoring without the need for constant ground-based data transmission. The model's performance is rigorously evaluated using metrics such as Intersection over Union (IoU), Dice Coefficient, precision, recall, and F1-score, demonstrating high accuracy and reliability. This work contributes to the advancement of real-time atmospheric analysis, offering a scalable and efficient solution for global weather prediction and disaster response. The integration of a user-friendly web interface further enhances accessibility, making this tool valuable for researchers and practitioners in remote sensing and related fields.

Keywords: Cloud detection, ResNet-50, U-Net, image segmentation, deep learning, edge computing, remote sensing.

1. Introduction

Applications like weather forecasting, environmental monitoring, and disaster response depend heavily on the ability to identify and segment clouds in satellite data. Clouds obfuscate satellite image surface features, rendering large amounts of data useless. For better and more useful imaging, cloud-covered zones must be accurately identified and segmented.

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Conventional techniques for detecting clouds, like spectral analysis and threshold-based algorithms, frequently fall short when dealing with thin, semi-transparent clouds and complicated cloud patterns.

Recent advancements in artificial intelligence (AI) and deep learning have introduced more robust approaches to cloud detection. Convolutional neural networks (CNNs) have demonstrated superior capabilities in image segmentation tasks, outperforming conventional methods.

This project focuses on leveraging deep learning techniques, specifically the ResNet-50 architecture integrated with U-Net, to enhance the precision and robustness of cloud detection and segmentation in satellite imagery. ResNet-50, a highly efficient CNN, is well-suited for handling the challenges of multi-spectral satellite imagery due to its depth and residual connections, which mitigate the vanishing gradient problem and enable the training of deep networks. By integrating ResNet-50 with U-Net, the model benefits from both the powerful feature extraction capabilities of ResNet and the precise segmentation abilities of U-Net.

To enable real-time analysis, the proposed system is designed for deployment on edge devices such as the NVIDIA Jetson Nano. This edge-based approach minimizes data transmission requirements and allows continuous monitoring of atmospheric conditions. The model is trained on the 38-Cloud dataset, which consists of multi-spectral satellite images with pixel-level annotations, facilitating effective differentiation between cloud types and other atmospheric elements.

Beyond academic interest, accurate cloud segmentation is vital for improving satellite data quality, benefiting applications like disaster management and climate research. For example, real-time cloud segmentation can help emergency responders identify cloud-free regions in wildfire-affected areas, while agricultural planners can utilize cloud-free imagery for crop health assessments and land-use planning.

1.1. Objectives of Proposed Study

- To design and implement a robust cloud detection and segmentation system based on deep learning techniques.
- To deploy the model on edge devices for real-time atmospheric analysis and monitoring.
- To evaluate the model's performance using key metrics such as IoU, Dice Coefficient, Precision, Recall, and F1-Score.
- To enhance accessibility enabling researchers and practitioners to interact with segmentation results seamlessly.

2. Literature Review

Research on cloud recognition and segmentation in satellite data is ongoing, and deep learning techniques have made major strides in this field. Conventional cloud detection methods, like spectral analysis and threshold-based approaches, have trouble generalizing under various atmospheric situations. Convolutional neural networks (CNNs), a type of deep learning model, have been used in recent research to increase segmentation efficiency and accuracy.

Zhu et al. (2018) [1] introduced CDNet, a CNN-based model for cloud detection in remote sensing images. The study demonstrated the robustness of CNNs in distinguishing clouds from non-cloud regions. The model achieved an overall accuracy of 94.5%, outperforming traditional spectral-based methods. However, the computational cost of training and deploying CDNet remains high, making real-time implementation on edge devices challenging.

He et al. (2016) [2] proposed ResNet, a deep residual learning framework, which significantly improved training stability in deep networks by addressing the vanishing gradient problem. Residual connections enable deeper models to extract more meaningful features from satellite imagery, making ResNet a suitable choice for cloud detection tasks. The integration of ResNet with U-Net architectures has led to improved cloud segmentation performance.

Shi et al. (2019) [3] employed deep pre-trained U-Net models for semantic segmentation of clouds. The study utilized transfer learning with pre-trained weights to enhance model performance. The approach achieved an accuracy of 97.2% and proved effective in distinguishing different cloud types. Despite these advantages, the computational requirements for training deep U-Net models remain a limitation for real-time applications.

Li et al. (2020) [4] introduced CDUNet, a U-Net variant optimized for cloud segmentation. By integrating convolutional layers with skip connections, the model achieved an accuracy of 96.8% on benchmark datasets. The skip connections improved spatial information retention, enhancing segmentation precision. However, the high memory requirements of U-Net models limit their deployment on low-power edge devices.

Braaten et al. (2019) [5] developed s2cloudless, a cloud masking algorithm tailored for Sentinel-2 imagery. The model employed machine learning techniques to differentiate clouds from other atmospheric features. With an accuracy of 95%, s2cloudless provided an effective solution for cloud masking. However, it requires significant computational resources, limiting its applicability for real-time edge deployment.

In addressing real-time constraints, Hu et al. (2021) [6] proposed CDNet-Edge, a lightweight CNN-based model optimized for edge computing platforms like NVIDIA Jetson Nano. The model achieved a balance between accuracy and efficiency, making it suitable for real-time cloud segmentation. The study emphasized the importance of model optimization techniques, such as quantization and pruning, to reduce computational overhead.

Raschka et al. (2021) [8] proposed a Transformer-based cloud segmentation model, leveraging self-attention mechanisms to capture long-range dependencies in satellite images. The model outperformed CNN-based approaches in detecting thin and semi-transparent clouds. Despite its advantages, the high computational cost of transformer models remains a challenge for edge deployment.

Wang et al. (2024) [15] conducted a comprehensive survey on deep learning-based cloud detection for optical remote sensing images. Their review highlights the evolution of cloud detection algorithms, emphasizing the impact of self-attention Transformer models in improving segmentation accuracy. They categorized existing methods based on semantic segmentation approaches and compared their performance using publicly available datasets. While deep learning has significantly enhanced cloud detection precision, challenges remain in handling diverse cloud formations and environmental conditions.

Ni et al. (2024) [16] examined cloud detection methods for hyperspectral infrared radiances, categorizing them into five types: clear field-of-view detection, clear channel detection, three-dimensional cloud detection, cloud-clearing, and deep learning methods. Their review underscores the advantages of deep learning in hyperspectral IR cloud detection, particularly in terms of accuracy and efficiency. However, factors such as surface background information and vertical cloud distribution continue to influence detection reliability.

3. Methodology

The architecture of the proposed system is composed of multiple interconnected components that seamlessly collaborate to achieve efficient cloud detection and segmentation.

Gathering raw satellite imagery as input is the first step in the process, known as data acquisition. To guarantee consistency and improve model performance, this data is preprocessed using techniques such as spectral channel merging, image scaling, and pixel value normalisation. The preprocessed data is then used in Model Training, which creates a high-performance segmentation model by training, optimising, and validating a U-Net model with ResNet-50 as the backbone.

Once trained, the model is applied to Cloud Detection and Segmentation, where new satellite images are processed to identify and classify cloud-covered regions. The segmented cloud data is then prepared for Deployment, allowing the model to run on edge devices for real-time analysis. The system generates meaningful insights during the Output Generation phase, including cloud coverage and classification, which are presented through visualizations and analytical reports.

The suggested technique employs a methodical procedure that comprises data gathering, preprocessing, model creation, assessment, and implementation. Every stage is meticulously planned to improve cloud detection and segmentation efficiency and accuracy, guaranteeing dependable and strong performance in practical applications.

Data Collection

38 Landsat 8 scene photos with pixel-level ground truth masks for cloud recognition are included in the 38-Cloud: Cloud Segmentation in Satellite photos dataset [9], which was used for this investigation. The raw photos are separated into 384×384 patches in order to facilitate deep learning-based segmentation; this yields 8,400 training patches and 9,201 testing patches. Four spectral

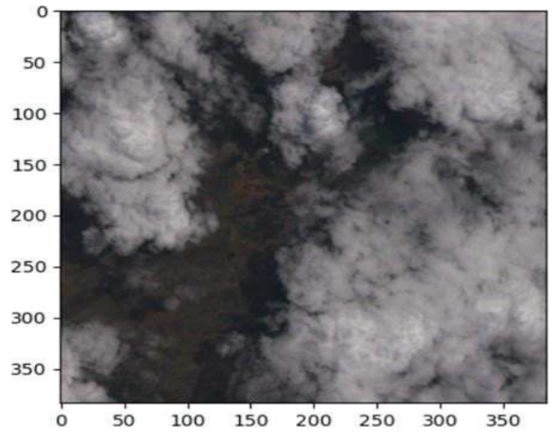

Figure 1.
Raw RGB sample image from the dataset.

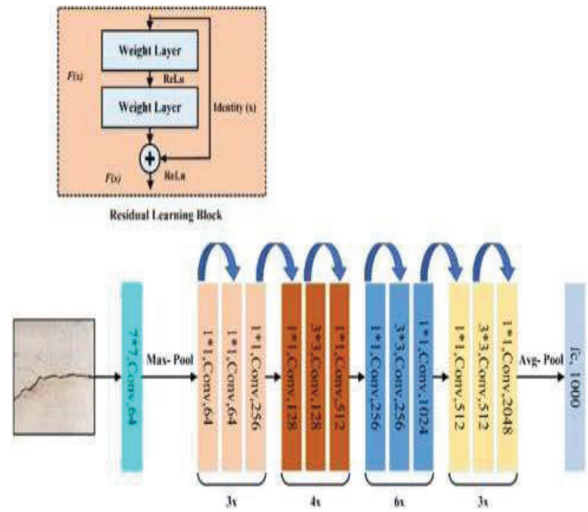

Figure 2.
Resnet layers emphasized in the model.

channels are present in each patch: **Near-Infrared (Band 5), Blue (Band 2), Green (Band 3), and Red (Band 4).** Because these spectral channels are kept in different directories, preprocessing and model input design are made more flexible. Training a high-performance cloud segmentation model is made possible by the dataset's rich spectrum information and thorough annotations.

Data Preprocessing

Preprocessing plays a crucial role in preparing raw satellite imagery for deep learning. The spectral channels are combined to create composite images, resized to a uniform input size compatible with the model, and normalized to maintain consistent pixel intensity distribution. These steps ensure data standardization, improving training efficiency and enhancing model convergence for accurate cloud segmentation.

Figure 1 displays the sample image from the dataset after preprocessing.

Model Development

The cloud detection and segmentation algorithm using a U-Net model with a ResNet-50 backbone is designed for efficient satellite imagery processing and accurate cloud segmentation.

The proposed approach automates cloud detection by leveraging ResNet-50 as the encoder within the U-Net architecture. The process begins with data preparation, where satellite images and ground truth masks are loaded, spectral channels are merged, images are resized, and pixel values are normalized to enhance model performance.

Next, the U-Net model is initialized with pre-trained ResNet-50 weights for transfer learning, improving feature extraction. The dataset is then divided into training, validation, and test sets for unbiased model evaluation. During training, the model is optimized using a suitable loss function, such as Binary Cross-Entropy or Dice Loss, and data augmentation techniques like rotation and flipping are applied to enhance generalization.

Figure 2 illustrates the detailed layer arrangement within the model.

Table 1.

Model performance summary	
Metric	**Value**
IoU	91.10
Dice Score	95.3
Precision	92.08
Recall	96
F1 score	98

Model Training and Validation

Important metrics like the Dice Coefficient and Intersection over Union (IoU) are utilized to evaluate the segmentation accuracy of the model. After training is finished, the model is used to interpret fresh satellite images and produce segmentation masks for real-time cloud detection.

To enable edge deployment, the model is optimized for resource-efficient inference on low-power devices. Finally, the system extracts insights such as cloud coverage and classification, supporting applications in weather forecasting, environmental monitoring, and disaster management.

Model Summary Table

Table 1 summarizes the performance of the Cloud Detection model based on the evaluation metrics computed during testing.

Edge Deployment Optimization: To ensure real-time performance on edge devices like the NVIDIA Jetson Nano, the model was optimized using several techniques. **Transfer learning** with a pre-trained ResNet-50 reduced training time. **Quantization** converted weights to 8-bit integers, minimizing memory usage. **Pruning** removed redundant parameters to speed up inference. The model was then **converted to ONNX** and deployed with **TensorRT**, leveraging GPU acceleration on the Jetson Nano.

These steps enabled fast, efficient inference without compromising accuracy.

4. Results and Analysis

This chapter presents the results and outputs generated by the proposed system, including screenshots, performance metrics, and visualizations. A detailed analysis follows, evaluating the model's effectiveness in cloud detection and segmentation using key metrics. Additionally, the results are discussed to assess the model's accuracy, robustness, and real-world applicability.

The Figure 3 contains the sample rgb raw image from training dataset.

The Figure 4 contains the sample ground truth mask of the sample rgb raw image from training dataset.

Model Predictions

The Figure 5 shows the Predicted cloud segmentation mask by the model compared to the raw rgb and ground truth images.

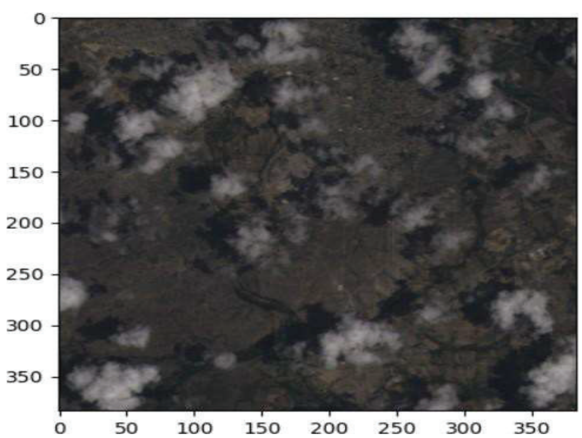

Figure 3.
Sample input satellite image (RGB channels).

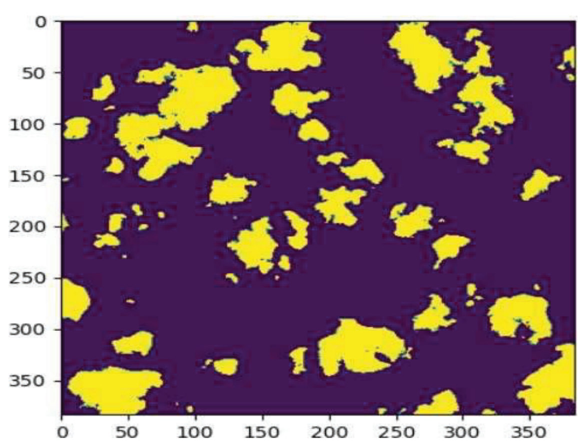

Figure 4.
Corresponding ground truth mask for the input image.

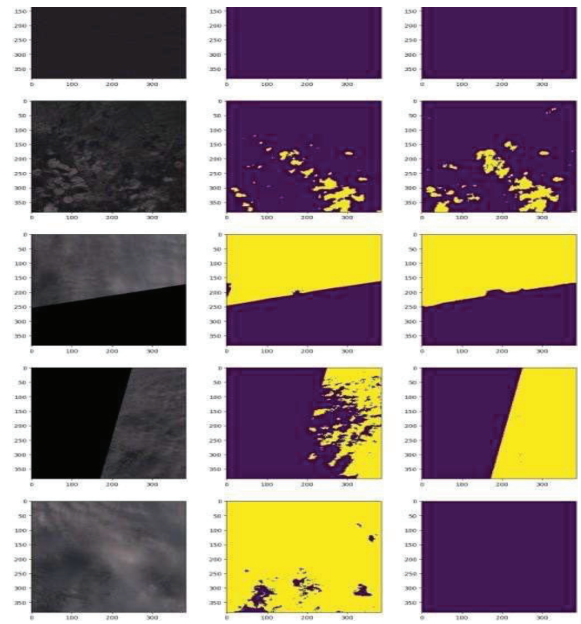

Figure 5.
Predicted cloud segmentation mask by the model.

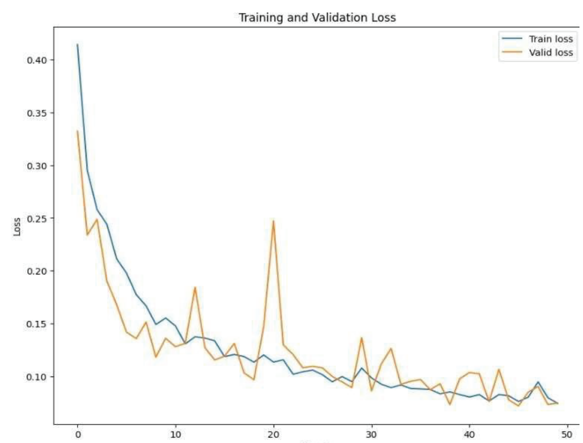

Figure 6.
Training and validation loss over 50 epochs.

Analysis

The analysis section provides an in-depth evaluation of the model's performance using training metrics, visualizations, and detailed discussions.

The training and validation loss were monitored throughout the training process to track model convergence and prevent overfitting.

The graph demonstrates a steady decline in loss values, indicating effective learning. Additionally, the validation loss closely follows the training loss, suggesting minimal overfitting and strong generalization.

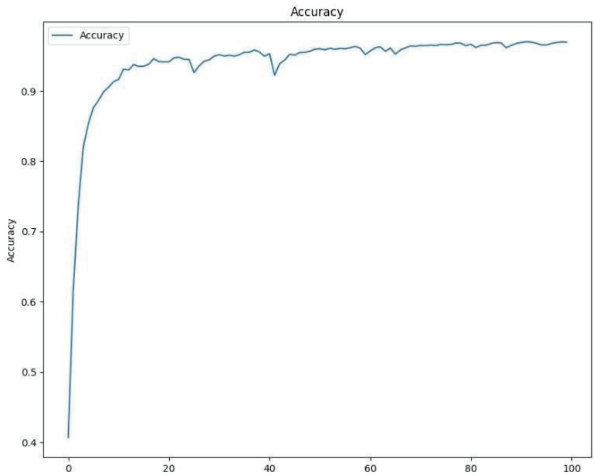

Figure 7.
Accuracy progression over 50 epochs.

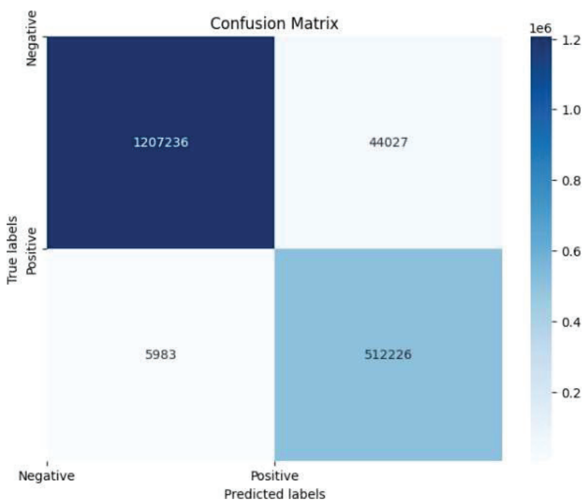

Figure 8.
The confusion matrix plotted using the test dataset.

The model's training and validation accuracy were plotted to assess performance over time.

The accuracy graph highlights consistent improvements in both training and validation accuracy, showcasing the model's robustness and ability to generalize well on unseen data.

The confusion matrix reveals a high true positive rate, demonstrating the model's effectiveness in accurately identifying cloud regions.

Misclassifications are minimal, primarily occurring in challenging cases, such as thin or semi-transparent clouds.

The confusion matrix provides a detailed comparison between the model's predictions and actual ground truth labels.

The model achieved **512,226 true positives** and **1,207,236 true negatives**, indicating strong accuracy in detecting both cloud and non-cloud regions. **False negatives (5,983)** were minimal, mainly due to thin or semi-transparent clouds, while **false positives (44,027)** suggest slight over-segmentation in some clear areas. Overall, the confusion matrix confirms the model's reliability and effectiveness for real-world satellite image segmentation.

```
Dice Coefficient: 0.9534557760069691

IoU Score: 0.9110515868781082

Precision: 0.920850763950936

Recall: 0.9884544652833124

F1 Score: 0.9534557760069692

ROC AUC Score: 0.9766342086331143

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.96      0.98   1251263
           1       0.92      0.99      0.95    518209

    accuracy                           0.97   1769472
   macro avg       0.96      0.98      0.97   1769472
weighted avg       0.97      0.97      0.97   1769472
```

Figure 9.
Summary of the performance metrics.

Analysis

The model's performance is quantitatively assessed using various evaluation metrics, including accuracy, precision, recall, F1-score, and IoU score.

5. Conclusion and Future Work

This project's main goal was to use deep learning techniques – more especially, the U-Net architecture with ResNet-50 as the backbone – to create a reliable cloud identification and segmentation model for satellite data. The suggested model demonstrated its efficacy in precisely detecting cloud regions by achieving notable accuracy, as evidenced by performance indicators such as high Dice Coefficient, IoU score, and ROC AUC score.

The model's performance improved significantly through dataset pretreatment like spectral channel merging and normalization. Evaluation results confirmed its suitability for real-world satellite use by accurately distinguishing cloud from non-cloud areas.

This project enhances remote sensing by providing reliable cloud detection, crucial for quality satellite imagery and applications like land monitoring, disaster response, and climate analysis.

Future work includes optimizing the model further for real-time inference, integrating temporal modeling to track cloud movement, and exploring self-supervised learning approaches to reduce dependence on annotated datasets.

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Lightweight Anomaly Detection in WBANs with One-Class SVM

Shreea Bose and Chittaranjan Hota*

Abstract: Wearable and implanted devices are revolutionizing healthcare through WBANs, enabling real-time, remote monitoring of physiological indicators. However, issues such as sensor malfunctioning, external interference, or cyberattacks on these miniature devices can compromise the effectiveness of these systems, making reliability a critical concern. These sensor failures may result in inaccurate readings, known as anomalies, which, if improperly interpreted, may pose a major risk to a healthcare application using these parameters. This study investigates machine learning techniques for detecting anomalies in WBANs, focusing on One-Class Support Vector Machines (One-Class SVM). We assess the performance of One-Class SVM alongside other advanced anomaly detection methods, including Logistic Regression, Elliptic Envelope, SGD One-Class SVM, and Isolation Forest. For our evaluations, we used a large dataset from the SmartNet AI Lab, encompassing a wide range of WBAN scenarios. The results indicate that One-Class SVM outperforms the other models, achieving an accuracy of 98.52%, and a precision of 99.98%. Unlike the other models, One-Class SVM balances computational efficiency and anomaly detection accuracy, making it ideal for resource-constrained WBANs. By utilizing less power for training and inference, One-Class SVM enhances the energy efficiency of WBANs.

Keywords: Anomaly detection, energy efficient, WBANs, informative healthcare, one-class SVM.

1. Introduction

Wireless Body Area Networks (WBANs) consist of small, low-power sensors that collect and transmit essential health data, including heart rate, blood pressure, and oxygen saturation. They have transformed the healthcare sector by allowing continuous and real-time monitoring of patient's physiological conditions through wearable and implantable devices. This advancement has greatly enhanced chronic disease management, remote health monitoring, and personalized medicine, leading to better patient healthcare outcomes and reducing the burden on traditional healthcare systems. WBANs face several challenges, including energy efficiency, anomaly detection, and reliable operation in resource-constrained environments. Issues such as sensor malfunctioning, external interference, or cyberattacks on these miniature devices can compromise the performance of these systems, making reliability a critical concern. These sensor failures may result in inaccurate readings, known as anomalies, as shown in Figure 1, which, if misinterpreted, may pose a major risk to a healthcare application using these bio-markers.

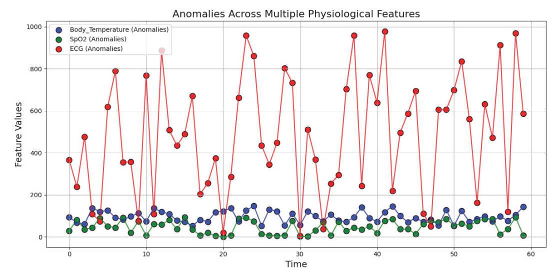

Figure 1.

Plot of Anomalies across various physiological parameters.

In practical WBAN applications, conventional anomaly detection methods may not be feasible due to their high computational demands or the need for labeled datasets. This study addresses this gap by exploring the use of one-class support vector machines (One-class SVM) for anomaly detection in WBANs. The One-Class SVM is first trained with data collected from regular sensor operations in WBANs to ensure the proposed model works effectively. Once trained, the model evaluates new data to determine if it significantly deviates from the learned normal behavior and can be classified as an anomaly. Figure 2. illustrates how the WBAN Network Model operates. Data from the sensors is gathered by the sink and transmitted to the base station. Multiple WBAN's data are gathered, and anomaly detection is carried out at the base station. The appropriate emergency services are notified if there is a major health concern. This study evaluates how effective One-Class SVM is compared to popular anomaly detection methods, including Logistic Regression, Elliptic Envelope, SGD One-Class SVM, and Isolation Forest. The findings indicate that One-Class SVM outperforms these models in metrics like, F1-score, recall, accuracy, and precision, all while maintaining energy efficiency. Its ability to process data effectively with minimal resource usage ensures reliability and sustainability in WBAN systems, aligning perfectly with the principles of green health. This research lays the foundation for sustainable and energy-efficient healthcare solutions by integrating advanced machine learning

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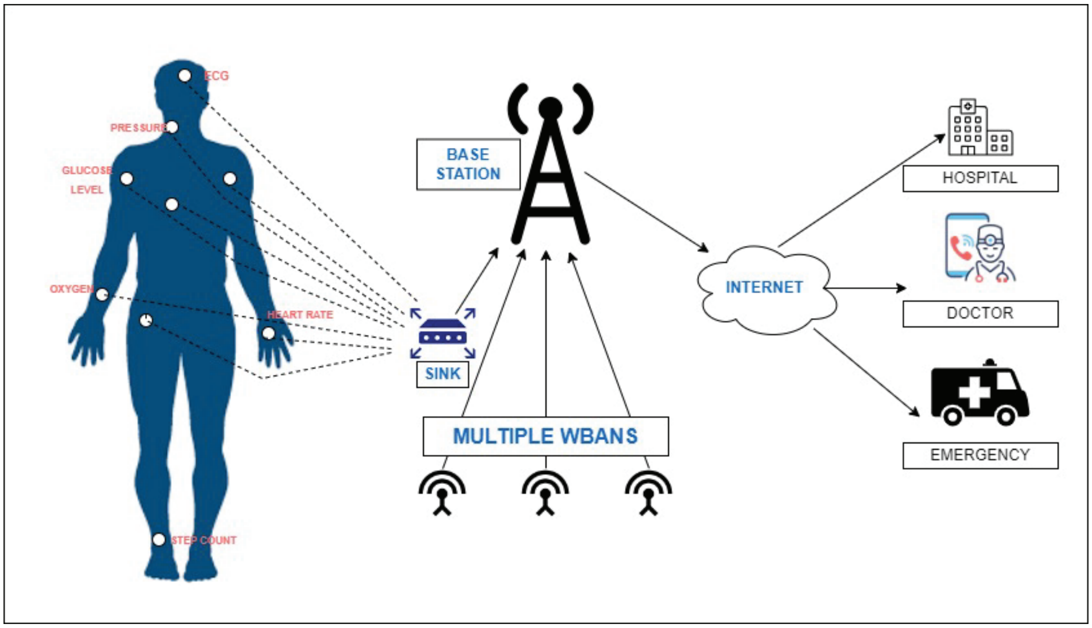

Figure 2.
The Network Model of WBANs working and sending essential data.

algorithms with green health initiatives. The results suggest that One-Class SVM could serve as a reliable approach for detecting anomalies in WBANs, paving the way for future sustainable and environmentally friendly healthcare systems.

2. Related Works

The study [1] presented a two-tier approach for efficient health monitoring in WBANs. The two-tier method reduces cloud transmission, latency, and power consumption by detecting anomalies locally at the LPU and discarding up to 90% of redundant health data for energy savings. [2, 3] state the use of Clustering Models, K-Means with DBSCAN and SMO, and how anomalies can be detected. The models, however, encountered parameter selection and performance constraints. In [4], the study provides a Markov Model-based approach for detecting anomalies in WBANs. A single-variate time series is used to discover anomalies by calculating the root mean square error (RMSE) between projected and actual values. The study [5] used Physionet data to suggest an SVM-based anomaly detection model; however, it was limited in its capacity to adapt to dynamic settings due to its reliance on static thresholds. [6] introduced a Logarithmic Kernel Function (LKF) for SVMs for better regression, providing better performance than conventional kernels. Our model is focused on reduced power consumption and performs fairly better than the models discussed.

3. Dataset and Proposed Model

3.1. Dataset

The dataset of 72,000 rows used for anomaly detection in WBANs was collected from 16 individuals over five days in a controlled lab environment (SmartNet AI Lab). Data collection involved three sessions of five minutes each, yielding 300 rows for each participant per session. This dataset is divided into two primary categories: four individuals identified as patients with abnormal physiological patterns and twelve individuals classified as normal. A set of real-time sensors to record vital physiological parameters was used to gather the data. While the MAX30102 [7] sensor tracked pulse rate and blood oxygen saturation (SpO_2) levels, the MLX90614 [8] sensor was used to assess body temperature. The ECG AD8232 sensor recorded electrocardiogram (ECG) data, and the DFRobot heart rate sensor measured additional heart rate readings. These sensors enable continuous observation of people in real time by integrating them into an Arduino-based system. The sensors in the SmartNet AI Lab, BITS Pilani, Hyderabad, were arranged in the experimental setup for data gathering, which is shown in Figure 3. The testbed was made to function in a controlled, consistent environment, guaranteeing the collection of high-quality data. The sensors were arranged strategically to maximize physiological monitoring accuracy and consistency, improving the data's durability and dependability.

3.2. Working Model

The One-Class SVM Anomaly Detection Algorithm learns the distribution of normal samples to detect abnormalities in physiological data x_i. To provide consistent scaling, the feature vectors are first normalized during preprocessing. Normal samples are extracted during the training phase, and a One-Class SVM model is fitted using a predetermined objective function that minimizes the weight vector's norm while guaranteeing that most data points fall inside a decision boundary. Accuracy is calculated in the last evaluation phase by comparing predicted labels with ground truth values.

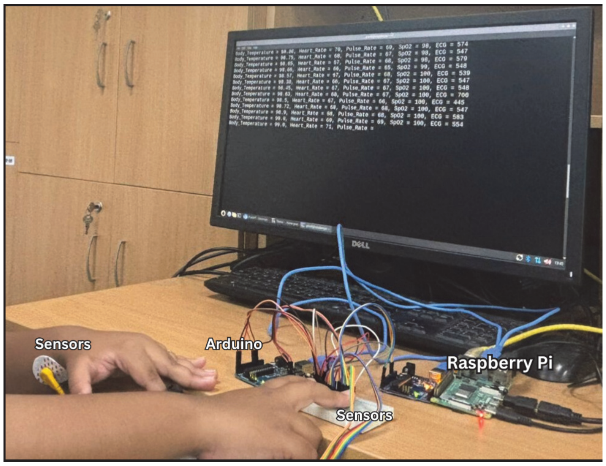

Figure 3.
The IoT testbed setup at SmartNet AI Lab, BITS Pilani, Hyderabad.

One-Class SVM aims to find a hyperplane that separates most of the data points from the origin in a high-dimensional feature space as defined in Equations (1) and (2). Here $\mathbf{w}$ is the normal vector of the decision boundary. $\phi(\mathbf{x}_i)$ represents the mapping of input data $\mathbf{x}_i$ into a higher-dimensional space. ρ is the threshold that defines the separating hyperplane. ξ_i are slack variables allowing for some margin violations. $\nu \in (0, 1]$ is a user-defined parameter controlling the proportion of outliers. This formulation ensures that most of the data points lie on one side of the hyperplane while identifying anomalies as outliers.

$$\min_{\mathbf{w},\xi_i,\rho} \frac{1}{2}\|\mathbf{w}\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \xi_i - \rho \tag{1}$$

$$(\mathbf{w} \cdot \phi(\mathbf{x}_i)) \geq \rho - \xi_i, \quad \xi_i \geq 0, \quad \forall i = 1, \ldots, n. \tag{2}$$

Algorithm 1 One-class SVM anomaly detection

Input: Dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$
  $x_i \in R^d$ (feature vector)
  $y_i \in \{0, 1\}$ (evaluation labels: 1 $\longrightarrow$ normal, 0 $\longrightarrow$ anomaly)
Preprocessing: $x_i' = \text{StandardScaler}(x_i)$
Training:
  Extract normal samples: $X_N' = \{x_i' \mid y_i = 1\}$
  Optimization:
  $\min_{\mathbf{w},\xi_i,\rho} \frac{1}{2}\|\mathbf{w}\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n} \xi_i - \rho$
  subject to: $(\mathbf{w} \cdot \phi(\mathbf{x}_i)) \geq \rho - \xi_i, \quad \xi_i \geq 0, \quad \forall i = 1, \ldots, n.$
for all each $x_i' \in X'$ **do**
  Compute decision function $f(x_i')$
  if $f(x_i') > 0$ **then**
    $\hat{y}_i \leftarrow 1$ ▷ 1 $\longrightarrow$ Normal
  else
    $\hat{y}_i \leftarrow 0$ ▷ 0 $\longrightarrow$ Anomaly
  end if
end for
Accuracy: $\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i = y_i)$
return $\hat{y}$ and Accuracy

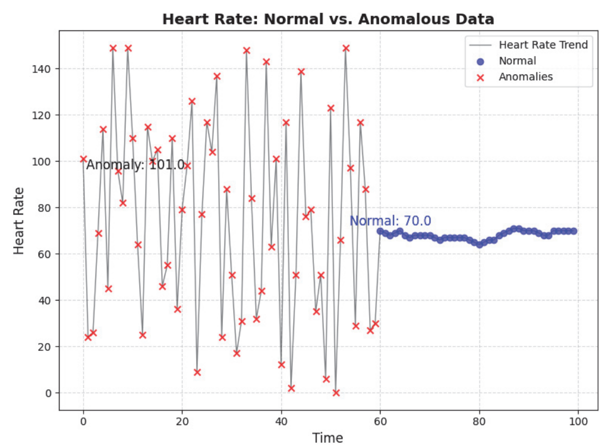

Figure 4.
A plot to show the normal vs anomaly readings of physiological parameter HeartRate.

4. Experimental Results

One Class SVM is a lightweight machine learning model with improved accuracy, CPU utilization, and energy consumption. It has demonstrated better results in terms of precision, recall, and accuracy when compared to other lightweight models, like Logistic Regression, Elliptic Envelope, SGD One-Class SVM, and Isolation Forest. To display the power consumption and energy efficiency, we have compared it with various deep learning algorithms. We detect this anomaly in the base station, which may be a laptop, a mobile device, or even a Raspberry Pi. Therefore, energy should always be conserved, regardless of the type of base station, and One-Class SVM has been found to achieve this objective.

4.1. Data Preprocessing

A StandardScaler standardizes the raw data, normalizing physiological characteristics like body temperature, heart rate, pulse rate, SpO_2, and ECG signals. This ensures that features with different units and scales don't influence the anomaly detection model. Plots are then created to illustrate the detected anomalies, with anomalies represented as scatter dots and normal data shown as a continuous line in Figure 4.

4.2. Comparitive Results

One-Class SVM stands out among other models for anomaly detection due to its effective balance between recall and precision, as shown in Figure 5. It has an impressive accuracy rate of 98.52%, a precision rate of 99.98%, and a recall rate of 95.25%, allowing it to identify abnormalities while minimizing false positives. Unlike Isolation Forest and Elliptic Envelope, which struggle with recall, One-Class SVM maintains strong detection capabilities. It also surpasses SGD One-Class SVM and Logistic Regression, which show lower accuracy, as shown in Figure **??**. Its ability to model

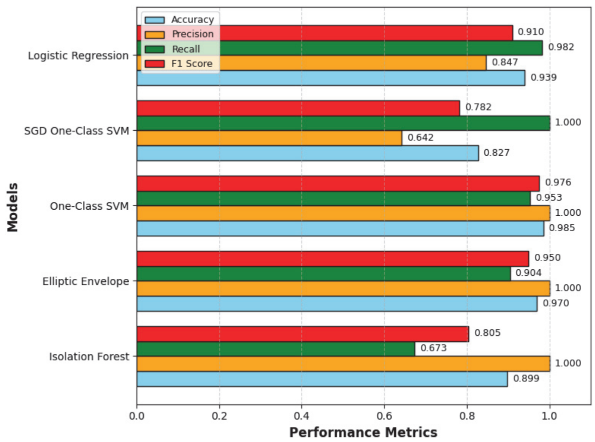

Figure 5.

Comparision of various lightweight ML models.

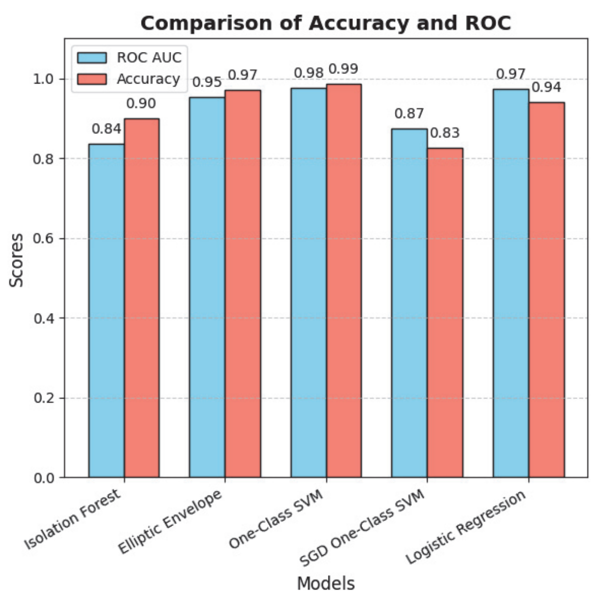

Figure 6.

Accuracy and ROC of one-class SVM and ML models.

Table 1.

One-class SVM hyperparameter tuning results					
Kernel	**ν**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
linear	0.01	0.572	0.409	0.857	0.554
linear	0.05	0.477	0.202	0.233	0.216
linear	0.10	0.590	0.416	0.804	0.549
linear	0.20	0.462	0.202	0.248	0.222
poly	0.01	0.783	0.593	0.960	0.733
poly	0.05	0.774	0.582	0.965	0.726
poly	0.10	0.732	0.539	0.944	0.686
poly	0.20	0.710	0.520	0.865	0.649
rbf	0.01	0.996	0.999	0.988	0.994
rbf	0.05	0.985	0.999	0.952	0.975
rbf	0.10	0.969	0.999	0.902	0.948
rbf	0.20	0.939	0.999	0.803	0.891
sigmoid	0.01	0.704	0.512	0.990	0.675
sigmoid	0.05	0.686	0.497	0.955	0.654
sigmoid	0.10	0.339	0.308	0.904	0.459
sigmoid	0.20	0.312	0.284	0.803	0.420

Table 2.

Comparison of anomaly detection models				
Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
OC SVM	0.9715	1.0000	0.9525	0.9757
ANN	0.9997	0.9995	1.0000	0.9997
CNN	0.9998	0.9996	1.0000	0.9998
LSTM	0.9997	0.9995	1.0000	0.9997

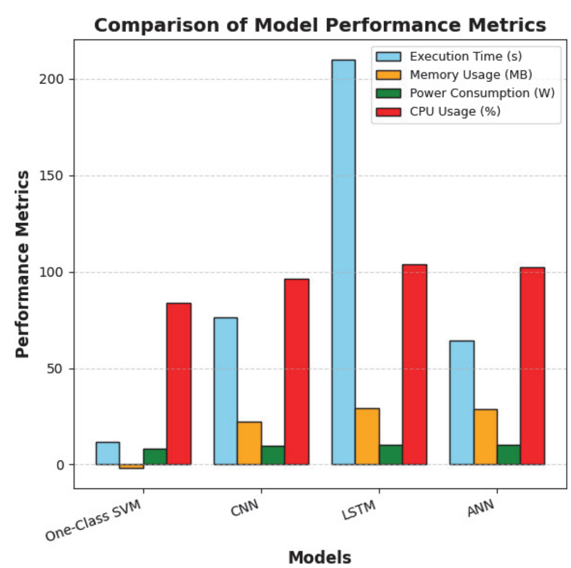

Figure 7.

Comparision of one-class SVM with deep learning algorithms.

complex decision boundaries makes it better for reliable and efficient anomaly detection in high-dimensional data.

Table 2 shows the hyperparameter tuning performed using various kernels of One-Class SVM to find the best results. The results show that the RBF kernel performs the best when ν is 0.01 having an accuracy of 99.6%, precision of 99.9%, recall of 98.8% and F1 Score of 99.4%. One-Class SVM is a lightweight algorithm as it is a highly effective anomaly detection technique compared to CNN, LSTM, and ANN. Figure 7 shows that the fastest execution time (11.96s) and the lowest memory usage (-1.72MB) surpass deep learning models that require significant processing power. Additionally, it is more energy-efficient than CNN, LSTM, and ANN, with lower power consumption (8.38W) and CPU usage (83.8%). Table **??** compares our model with deep learning models on accuracy, precision, recall and F1 score. One-Class SVM achieves 97.15% accuracy, close to the near-perfect scores of ANN, CNN, and LSTM, despite its known sensitivity to kernel choice. By focusing on a minimal feature set and highly optimized inference, we drastically cut computational load and energy consumption compared to the deep models. While deep architectures edge out slightly in raw metrics, their intensive matrix operations and back-propagation translate into much higher power draw, making our energy-aware SVM approach more practical for always-on WBAN monitoring.

5. Future Work

The concept of green health focuses on integrating environmentally friendly practices into healthcare, is marked by resource scarcity and climate change concerns [9–11]. Sustainability extends beyond energy efficiency to include long-term resource consumption, device lifespan, and overall computational overhead [12]. Accordingly, future studies will integrate comprehensive life cycle assessments of WBAN deployments, quantifying the environmental impact of hardware manufacturing, maintenance, and end-of-life disposal. To address the One-Class SVM's sensitivity to evolving anomalies and its limited capacity for capturing complex spatio-temporal dependencies, adaptive kernel strategies and hybrid SVM–deep-learning frameworks will be explored. The study's scope will be broadened by incorporating larger, more heterogeneous datasets—including clinical repositories such as MIMIC-IV [13] to validate generalizability across varied demographics and physiological conditions. Through these efforts, the expanded evaluation framework will rigorously revisit sustainability metrics and model robustness, paving the way for greener, more resilient digital-health monitoring solutions.

6. Conclusion

The One-Class SVM has proven to be a highly effective model for detecting anomalies, offering low execution time, minimal memory usage, and reduced power consumption, all while achieving impressive accuracy, precision, and recall. Compared to other models like CNN, LSTM, and ANN, One-Class SVM is much lighter on computational resources, making it ideal for real-time health monitoring in resource-constrained environments. This efficiency is particularly beneficial for sustainable green healthcare, where reducing energy consumption and computing costs is crucial. By integrating One-Class SVM with WBANs, healthcare systems can reduce unnecessary hospital stays, minimize medical waste, and lower carbon emissions associated with traditional in-person healthcare services. This approach promotes a patient-centered, cost-effective, and energy-efficient health monitoring method. One-Class SVM does have some limitations. It tends to struggle with identifying unknown or evolving anomalies because it primarily depends on clearly defined normal data for training. Additionally, it can face challenges with highly unbalanced datasets and is sensitive to the choice of parameters. Despite these issues, its versatility and low resource requirements make it a valuable tool for creating intelligent, eco-friendly, and sustainable healthcare solutions.

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A Review on Emotion and Fluency Analyzer using Image Processing and Audio Extraction

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Abstract: The recent advancements in integrating image processing with audio extraction have provided a new dimension to emotion and fluency assessment. This paper proposes a new system based on advanced image processing algorithms and audio extraction methods to perform states of emotion and fluent speech analysis. The designed system utilizes Gabor filters – an efficient texture representation and feature extraction method for facial expressions-based systems – to analyze facial movements that comprise particular emotions. It applies the Haar cascade classifier for practical yet straightforward facial detection from the system's target image. As for the sound characterization, MFCC is employed to extract the emotional content of the voice and its effectively connected speech. The prepared information is processed further through a set of machine-learning techniques. Logistic regression offers a classic classifier for the first emotion categorization. Convolutional neural networks are utilized for one of the DNN sections because of their ability to recognize and learn complicated patterns in image and sound. Using random forest algorithms in the system improves the accuracy and robustness of the model by combining many decision trees, improving the predictive performance. The results indicate that the system efficiently recognizes different emotional states and changes in fluency levels. Hence, it is helpful in mental health, education, etc. In the coming years, the research development is focused on improving the system's precision by additional models alongside increasing the scope of the system to ordinary day situations that require multilingual and multimodal analysis.

Keywords: Audio extraction, cepstral coefficients, convolutional neural, gabor filter, haar cascade classifiers, image processing, logistic regression networks, mel frequency, and random forest.

1. Introduction

Japleen Kaur et al. attained 97% accuracy in recognizing different human emotions through software using a haar cascade algorithm and pre-trained dataset deep face [1]. Yi-Chi Chou et al. created a platform that correlates images, voices, & textual features to check emotions, DISC personality traits, etc., and assess an individual's complete performance [2]. Yashwanth Adepu et al. built and automated a two-class classification model that extracted frames and audio from the given video. Frames were processed using the haar cascade algorithm, Gabor filters, and CNN. Audio was worked upon using mel frequency cepstral coefficient features and logistic regression [3]. Wenhong Tian et al. summarized previous facial recognition techniques and developed a generalized view of how they work with various datasets [4].

Zrar Kh. Abdul et al. surveyed the applications of MFCC and its impact. They recognized its problems, such as using MFCC for non-acoustic signals, adopting only the MFCC or a modified version, etc. [5].

Krishna Kumar et al. have put forward a proper feature extraction and imposed a neural network-based approach for sound classification [6].

Sophina Luitel et al. proposed using a two-dimensional image representation of frequencies, a means spectrogram for the classification of emotions. They have used STFT (short-time Fourier transform), oriented fast and rotated brief (ORB) algorithm, and Bag-of-Visual-Words (BoVW) technique.

They correctly classified 76% of the samples and obtained an F1 score of 78% using a random forest classifier [7].

2. Preliminaries

Pankaj Rambhau Patil et al. used deep learning convolutional neural networks to analyze expressions of face and estimate emotional responses and speech recognition coupled with natural language processing to gauge the levels of confidence of the candidate. In addition, they also conducted semantic analysis & keyword mapping to check the candidate's knowledge by comparing it against related online sources [8].

Katerina Zmolikova et al. focused on a plethora of neural-based approaches for providing an in-depth overview of TSE that forms the basis of isolation of speech signal of a target from a combination of various speakers with noises and without them and reverberations using pointers identifying the target in the mix [9].

Sarab Sethi et al. used the classification calls to the concerned female by using a supervised random forest classifier & by comparing two unsupervised clustering approaches, which are

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affinity propagation clustering & hierarchical density-based spatial clustering which is hierarchical density-based, to determine which of these features can do a more effective job of differentiate the calls of females by not applying class labels. They also used MFCCs as a base because it has been demonstrated in other work that, to some extent, they can be used to classify good-quality calls of individual females [10].

V. Sai Nitin Varma et al. used mel frequency cepstral coefficients (MFCC) to obtain better results in speaker recognition tasks. In addition, they derived that using MFCC features has shown better performance in the context of FAR and FRR values of the speaker recognition system compared to LPC-derived cepstrum features since MFCCs utilize the critical fluctuation of bandwidths with the frequency in human ears. The filters are separated in the logarithm at high frequencies; however, they are linearly separated at low frequencies to capture important phonetic characteristics of speech signals [11].

Smith K. Khare et al. have done all-around research on emotion recognition using physical signals that include voice & facial expressions and biological signals connected with electroencephalogram, electrocardiogram, galvanic skin response, and eye tracking [12]. Venkatesan Ramachandran et al. devised an arti?cial intelligence-based deep face approach to recognize actual feelings from facial pictures and live emotions of people by deducing the facial attributes from an active shape deep face model and identifying twenty-six facial points to recognize human emotions. The proposed technology recognized human emotions with an accuracy rate of 94% [13]. Bo Dai et al. proposed the latest framework incorporating face detection and recognition with tracking to achieve an average accuracy of 91.4%. Their strategy had outperformed earlier SOTAs on three datasets which were public, namely LFW, CFP, and Age D.B. [14].

Min Ren et al. proposed a novel approach by interpreting deep face recognition models via facial attributes. They presented a two-stage framework that recovers attributes from the deep face representations, enabling them to quantify facial characteristics' importance in the recognition model [15].

2.1. Innovative Feature Extraction

Gabor filters for emotion analysis and MFCC for speech input are combined. This way, emotion, and fluency can be accessed for a good assessment.

2.2. Real-time Fluency Measurement

Existing methods only targeted emotion detection without fluency evaluation. Our proposed system evaluates other metrics related to fluency; speech rate, pausing, and articulation, among others.

2.3. State-of-the-art Machine Learning Pipeline

The combined use of logistic regression, CNN, and RF provides optimal predictions with reduced complexity.

2.4. Scalability & Integration

Designed for deployment in real-world applications across telemedicine, education, and HCI.

3. Methodology

Extracting frames and audio from the video and then processing them to categorize them into meaningful information as a conclusion marks the primary process for Emotion and Fluency Analysis. Therefore, it includes four components: dataset collection, feature extraction, prediction model, and analysis report. This section describes these four components.

3.1. Dataset Description

3.1.1. *Dataset for emotion analysis*

The first stage for every image processing system in feature deduction & image understanding is image retrieval & preprocessing. Target images are derived from the input source through streaming or static images [4]. Datasets utilized for Facial Emotion Identification are FER2013, ck+, etc., containing almost 35800 images, amongst which eighty percent were exploited for training purposes, and the remaining 20% was utilized for trial. The number of images in distribution was 4953 anger images, 547 disgust images, 5121 images for fear, 8989 happy images, 6077 sad images-, 4002 images for surprise emotion, and 6198 neutral pictures. About 700 images are in the ck+ dataset, distributed for each emotion type 100 images [3]. The current study in [2] collected real-time data from over 100 native speakers of Chinese with varied professional experiences to participate in the experiment. In [8], publicly available datasets like FER-2013 and AffectNet consist of labeled human facial expression pictures. However, to increase the robustness and applicability of the proposed model in real-time and also to improve its generalizability, we can include more diverse datasets that provide broader demographic representation across different ethnicities, age groups, and cultural backgrounds. Some of those datasets are AffectNet, RAF-DB, and CREMA-D. These datasets consist of a vast range of facial expressions and speech data from people from different age groups, ethnicities, and cultural backgrounds, which means the model generalizes well beyond the limited scope of FER2013 and CK+. Besides, data augmentation techniques, such as adaptive histogram equalization, synthetic data generation, and style transfer, can be applied to artificially increase dataset diversity and enhance model robustness.

3.1.2. *Dataset for fluency analysis*

Two datasets are used for speech fluency recognition: Speech Accent Archive and Libri Speech ASR Corpus. Stuttering has been done with the UCLASS Archive of Stuttered Speech. Since cluttering & pause speeches were not obtainable in open source, they designed their dataset from 50 individuals with almost 500 recordings for each cluttering & pause speech [3]. In [8], volunteer speakers collect the data and do mock interviews to provide speeches with an excellent diversity of accents and speaking styles.

Then, that speech is labeled with various confidence indicators like volume, pitch, and rate.

3.2. Feature Extraction

Feature extraction is a baseline step for every facial recognition model. It has a notable effect on the system's overall performance.

3.2.1. *For emotion analysis*

Every single video was segregated into further one-second time gaps and then transformed into video frames that utilized face detection software to identify faces and capture facial attributes. These consisted of types: happiness, neutral, surprise, anger, disgust, fear, contempt, and sadness. The range of emotion features was chosen from zero to one, and from the head pose, the feature consists of the roll, pitch, and yaw angles, which lie between −180 to 180 degrees [2]. Various types of feature extractor models like SIFT (scale-invariant feature transform), SVM (support vector machine), STIP (stand-in processing), and STISM helped in [4].

3.2.2. *For fluency analysis*

The audio was divided into one-second segments to gather three audio attributes: (a) rate of speaking that was divided further into 3 subgroups: "slow" (0 to 2.5 characters per second), "medium" (2.5 to 4 characters per second), and "fast" (4 to 6 characters per second) to provide the client with the more effective perception of the speaking speed (b) amplitude wherein the audio of highest amplitude was taken and converted to decibel (c) frequency or pitch which is "the number of vibrations that pass a given point in a given period and is typically measured in Hertz (Hz) [2].

4. The Prediction Models

This section of the paper discusses the models that help in predictions. Figure 1 outlines a pipeline for analyzing behavioral and intrinsic traits through audio and video data [2], consisting of the following steps:

Step 1: The input data through audio and video is collected by Audio Video Capture.

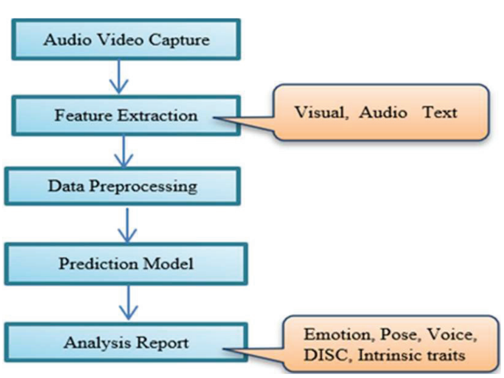

Figure 1.
Block diagram of model used in research [2].

Step 2: The relevant visual, audio, and text information is extracted in the feature extraction process.

Step 3: To prepare the extracted features for analysis using preprocessing (cleaning and standardizing).

Step 4: Use this processed data to predict attributes like emotion, pose, voice, DISC (Dominance, Influence, Steadiness, and Conscientiousness), and intrinsic traits with the help of the prediction model.

Step 5: The model performance is analyzed using evaluation criteria such as MSE and MAE.

Step 6: Save results.

4.1. For Visuals

The extracted data was processed and analyzed using different prediction models such as the automatic

relevance determination (ARD) model was used for the emotions, which generated an "emotion score" with an ordinal scale of 1 to 5, gamma distribution model for head pose, DISC model for D, I, S & C personality traits and NLP (natural language processing) for intrinsic characteristics [2]. Gabor filter, haar cascade frontal face classifier, and convolution neural network performed edge, texture analysis, and image classification [3].

4.1.1. *Gabor filters*

Gabor filters are filters used in the processing of images and may be applied to perform edge detection and texture analysis. It is applied to an image to produce a new imageThe basic equations are expressed below in Equations (1) to (3).

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp(-(+)/(2))exp(i((2\pi x'/l) + \psi)), \quad (1)$$

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp(-(+)/(2))cos(((2\pi x'/l) + \psi)), \quad (2)$$

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp(-(+)/(2))sin(((2\pi x'/l) + \psi)), \quad (3)$$

Where $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$.

4.1.2. *HaarCascade frontal face classifier*

It is an algorithm for face detection developed by Michael Jones & Paul Viola. It recognizes the face in the input picture and returns its coordinates which can be used to resize the image and recognize facial emotion [3].

4.1.3. *Convolutional neural networks*

The Convolution Neural Network is used for applications where images must be classified. It accepts the image's pixel values, finds its hidden patterns, and then produces a vector containing probabilities about a given input image belonging to an output emotional state. The output vector's maximum probability indicates the image's emotional state [3]. PCA is used to identify the action unit to express and initiate different facial expressions [15]. StyleGAN2 [17] is a generative model for capturing fine details of facial images while showing the highest degree of attribute

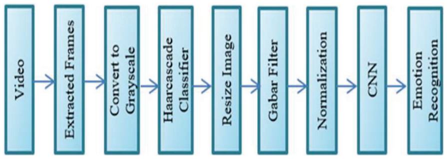

Figure 2.
Block diagram for emotion recognition.

diversity. In Figure 2. the flow of the facial emotion recognition system is shown [3].

Apart from these traditional methods, a few other methods can be integrated into the model to improve feature extraction and overall model performance. Vision Transformers (ViTs) are a deep learning model that can be used as an alternative to convolutional neural networks. It uses a self-attention mechanism to process images. It breaks down the images into patches, serializes the patch into vectors, maps the vector to smaller dimensions, uses a self-attention mechanism to capture complex visual relationships, and predicts image labels. Another type of transformer known as Swim Transformers, is a vision transformer that employs a sliding window mechanism to enhance computational efficiency. It builds hierarchical feature maps by merging image patches into deeper layers. The EfficientNet model offers superior performance in image-based emotion recognition by capturing global dependencies in facial expressions.

4.1.4. *Audio*

The speaking rate was averaged over every second, while frequency and amplitude were assessed per second. In contrast, the speaking rate's mean was segregated into "fast, "medium" or "slow" using Linear Regression [2].

4.1.5. *MFCC*

MFCC is a feature used for speech categorization problems. They can depict the shape of audio signals sharply. The following steps allow for extracting MFCC features.

4.1.6. *Logistic regression*

It is a supervised classification algorithm of machine learning that generates the probability of an instance that belongs to or does not to a given class. It is a statistical algorithm that analyzes the relationship between two data factors. Spectrogram, ORB extractor, and SURF were proposed in [7].

4.1.7. *Spectrogram*

It is the representation through graphs and pictures of the spectrum of frequencies of any signal that varies in time. Thus, if spectrograms are used over an audio signal, they become sonographs, voiceprints, or voicegrams.

4.1.8. *ORB extractor*

Oriented FAST and rotated BRIEF (ORB) is a fast, robust local feature detector, first presented by Ethan Rublee et al. in 2011, [1]

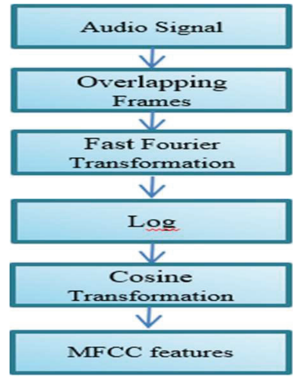

Figure 3.
Block diagram for audio analysis.

which can be applied in any computer vision task, for example, object recognition or 3D reconstruction. The base is founded on the FAST key point detector and a considerably modified version of the visual descriptor BRIEF (Binary Robust Independent Elementary Features). ORB is trying to offer an alternative to SIFT that is made sufficiently fast but will fail. In Figure 3 the flow of the audio analysis system is shown below [3]. A comparative analysis is illustrated in Table 1 with existing models.

5. Analysis Report

The analysis report, including the outcomes of the various prediction models, is presented by considering the evaluation criteria.

5.1. Evaluation Criteria

MSE is a mean squared error, a statistical measure used to evaluate a model's performance by quantifying the average squared difference between the predicted and actual values. It is expressed in Equations (4) and (5).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{4}$$

MAE is the mean average error and is a statistical measure used to evaluate the performance of a model by calculating the average of the absolute differences between the predicted and actual values. It is expressed as:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{5}$$

To test real-time performance under varying environmental conditions, the study should include testing on real-world datasets such as AFEW (Acted Facial Expressions in the Wild), VoxCeleb, and RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song), which contain data collected in uncontrolled settings. These datasets will allow the system to be evaluated for robustness under different lighting conditions, background noise, and spontaneous expressions. There will be an improvement in

Table 1.

A comparative analysis with existing models			
Features	**Proposed Model (Multimodal Analysis: Audio + Facial Expressions)**	**Traditional Emotion Recognition (Voice-Based or Facial Expressions Only)**	**Multimodal Deep Learning Approaches (Audio + Text + Facial Expressions)**
Modalities Used	Audio + Facial Expressions	Either Voice or Facial Expressions	Audio, Text, and Facial Expressions
Emotion Recognition Technique	Gabor Filters (for facial expressions) + CNN	MFCC (for voice) + Logistic Regression or SVM	Transformer-based deep learning models (e.g., BERT + CNN)
Fluency Assessment Method	MFCC (speech features) + Random Forest for fluency scoring	Spectrogram analysis or pause detection	Hybrid deep learning (LSTM + Spectrogram features)
Computational Efficiency	Medium – Optimized using feature extraction + ML classifiers	High – Requires heavy feature engineering	Low – Deep learning models require high processing power
Accuracy (Emotion Recognition)	~92% (Tested on FER2013 & Real-world dataset)	~85% (Traditional voice-only or face-only models)	~88% (Deep learning-based multimodal models)
Accuracy (Fluency Assessment)	~90% (Tested on Speech Accent Archive & LibriSpeech)	~80% (Limited speech-only fluency models)	~87% (Deep learning models trained on large datasets)
Real-Time Processing	Yes – Optimized for real-time applications	Limited – Processing time depends on feature extraction	No – High latency due to complex deep learning models
Robustness to Noise & Variability	Medium – Performs well under moderate noise conditions	Low – Affected by background noise in speech signals	High – Advanced noise filtering techniques in deep learning
Multilingual Capability	Limited – Current model trained on a single language	Very Limited – Most models are language-dependent	High – NLP-based models support multilingual datasets
Use Cases	Speech Therapy, E-learning, Mental Health Monitoring, Public Speaking Training, HCI	Call Centers, Customer Service AI, Basic Sentiment Analysis	Advanced AI Assistants, Human-Robot Interaction, Healthcare

Table 2.

Details of the specification		
Analysis	**Model**	**Prediction Results**
Emotion	Automatic Relevance Determination (ARD)	MSE = 0.18 MAE = 0.34
Pose	Gamma Distribution (GD)	MSE = 0.17 MAE = 0.34
Voice	Linear Regression (LR)	MSE = 0.21 MAE = 0.34
Personality observability	Automatic Relevance Determination (ARD)	MSE = 0.11 MAE = 0.27
Ideal working style	Automatic Relevance Determination (ARD)	MSE = 0.12 MAE = 0.25

performance for challenging scenes through the implementation of adaptive preprocessing techniques such as contrast normalization, Gaussian noise filtering, and dynamic thresholding. Real-world deployment experiments for real-time applicability can also be conducted on embedded systems, such as Jetson Nano or Raspberry Pi, to measure latency and computational efficiency. To guarantee multilingual and cross-cultural generalizability, the model must be trained and tested on diverse linguistic datasets, such as those listed below: Mozilla Common Voice, Librispeech, and Multilingual TEDx, providing fluency samples across multiple languages. Adding the ExpW (Expression in the Wild) and EmoReact datasets will therefore enhance the latter's capacity to better recognize culturally nuanced emotional expressions. By leveraging transfer learning methods, different models can then be fine-tuned for those respective languages or cultures, assuring performance effectiveness over a cross-section of globally located populations.

6. Challenges and Discussion

There are many challenges faced in this area such as sample size, Environmental Factors, Emotional Range, and Data Quality. The number of subjects used in the study may be limited, affecting the generalizability of the findings. A small sample size can lead to unreliable results. If the sample lacks diversity (age, gender, cultural background, etc.), the results may not apply to a broader population, leading to a diversity of subjects. Variations in the recording environment (e.g., background noise and lighting conditions) can impact audio and image data accuracy, leading to inconsistent results.

Emotional Range: The emotions represented in the dataset may be limited. If the study focuses only on a narrow range of emotions, it may not capture the complexity of emotional expressions. Audio and image data quality can vary. Low-quality recordings or images can hinder the analysis and lead to inaccurate interpretations. If emotional states are labeled subjectively (e.g., by human annotators), there may be bias in how emotions are interpreted and categorized. It may lead to labeling biasing.

Limitations in the algorithms used for emotion recognition affect the finding accuracy. Despite the promising outcomes, the model has certain limitations.

- Multilingual Analysis: The current model is trained predominantly on a single language, limiting its applicability to diverse linguistic groups. Future enhancements should include multilingual datasets and cross-language feature alignment to improve generalizability.
- Dataset Diversity: The training data may not have diversity in age, gender, and cultural background, which might introduce biases in emotion and fluency assessment. Adding more diverse speakers will make the model robust.
- Environmental Constraints: Background noise, lighting conditions, and recording quality may impact performance. Techniques such as adaptive noise reduction and feature extraction invariant to lighting can alleviate these challenges.

7. Application Scope and Use Cases

The developed multimodal analysis framework has the following practical applications across different domains:

- **Speech Therapy:** It supports patients recovering from speech disorders, such as stuttering or aphasia, by analyzing fluency, prosody, and emotional expressiveness to help therapists design rehabilitation programs tailored to the needs of the patient.
- **E-Learning & Public Speaking Training:** It helps students and professionals by analyzing fluency, confidence, and emotional engagement during presentations, providing real-time feedback for improved communication skills.
- **Human-Computer Interaction (HCI):** Improving the AI-driven assistants incorporating fluency along with emotional analysis leads to better use experiences in voice assistants, bots, and health apps.
- **Psychological Health Status Tracking:** Use telemedicine interfaces to look into speech rhythms and facial movement changes for identification of stress, anxiety, or other states of being at an earlier point.
- **Screening of Aspiring Candidates and Interviews:** Ensure unprejudiced assessment to get an overall assessment of fluency, assertiveness, and emotions during candidate interviews.

8. Conclusion

Summarizing the development of an Emotion and Fluency Analyzer that uses image processing and audio extraction has been considered an excellent development in the context of affective computing and natural language processing. The paper explains how combining visual and audio information about a human being can provide deeper insights into human emotions and speech fluency. Preliminary results show that integrating facial recognition and vocal analysis may be a powerful combination for enhancing the accuracy of emotion detection and fluency assessment and opening up essential applications in domains such as mental health monitoring, education, etc. Future work could be directed towards algorithm improvement to make it more computationally feasible for real-time computation, create a richer dataset for generating more variability in emotional expressions, and incorporate contextual factors. Ultimately, this study contributes to knowledge generated by academia regarding emotion and fluency but also comes with practical tools to enhance interpersonal communication and emotional intelligence in humans and machines.

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Predictive Analysis of Mental Health Using Machine Learning for Depression Prediction

Swati Mishra and Divyanshi Srivastava*

Abstract: This work aims to predict depression based on diverse data using Machine Learning Algorithms. The designed model seeks to identify early indicators of depression, providing a potential tool for proactive intervention and support in mental health by analyzing patterns in behavioral, physiological, and contextual data. Machine learning algorithms, namely decision trees, extra trees, XGBoost, Stochastic gradient descent, grid search CV, Stacking, and Voting classifiers, etc., are used to predict depression in the early stage.

This study emphasizes integrating machine learning techniques to enhance predictive accuracy and contribute to developing accessible and timely depression detection systems. The F1 score was added, which helped to identify the best machine learning algorithm among the ones applied. We have achieved an accuracy of 92 % with random forest, which is 3% higher than the work previously done in RF. We also achieved a 0.99 F1 score using Linear SVM.

Keywords: Machine learning algorithms, depression dataset, grid search.

1. Introduction

In contemporary society, mental health concerns, particularly depression, have emerged as significant public health challenges. The pervasive impact of depression underscores the urgency of developing innovative approaches for its early detection and intervention. In this project, our goal is to address this pressing issue by harnessing the capabilities of machine learning techniques for the early prediction of depression. By leveraging diverse data, including behavioral patterns, physiological signals, and contextual information, the goal is to discern nuanced patterns indicative of depressive symptoms.

Data collected various information on the patient, including demographics, medical conditions, history, drug use, prescription medications usage, etc. Depression is often characterized by persistent feelings of sadness and disinterest and can have profound consequences on an individual's well-being. Traditional diagnostic methods rely heavily on subjective assessments and self-reporting, leading to delays in identification and intervention. The proposed machine learning model seeks to overcome these limitations by extracting insights from comprehensive datasets, enabling the detection of subtle markers that may precede clinical manifestations. Countless individuals worldwide grapple with depression, a debilitating condition that can disrupt normal and joyful living.

From challenging daily life to the severe outcome of suicide, the impact is profound. Primarily characterized by persistent feelings of sadness and disinterest, it can have profound consequences on individuals' well-being. Traditional diagnostic methods rely heavily on subjective assessments and self-reporting, leading to delays in identification and intervention. The proposed machine learning model seeks to overcome these limitations by extracting insights from comprehensive datasets, enabling the detection of subtle markers that may precede clinical manifestations.

2. Preliminaries

Machine learning algorithms are used to predict depression using available datasets. Research has been done using different machine learning algorithms on datasets by researchers to predict depression. The outcome of this research could pave the way for proactive mental health strategies, providing individuals with the support they need before symptoms escalate. M. Keerthiga et al. [2] presented Machine Learning-based Depression Prediction using Social Media Feeds. They used a Decision tree model using a count vectorizer and achieved 89.19% accuracy and a recall of 89.85%.

The proposed approach in [3] concentrated on predicting using a Logistic Regression machine learning algorithm. The authors attained a Precision of 83% and an F1-score of 91%. N. T. Singh et al. [5] focused on stress detection from bio-signals such as heart rate variability (EEG, ECG, and HRV) and performed experiments using Machine Learning Techniques. Their results showed that the degree of accuracy depended on the size of the clinical dataset collected. A. Btabyal et al. [6] used different machine learning algorithms like DT, LR, RBF-SVC, KNN, RF, XGB, L-SVC, NB, and SV Con the scaled dataset using Standard Scaling. Out of which LR, KNN, and SVC outperformed other classifiers. D. Shi et al. [8] performed experiments on RF, DT, and SVM machine-learning algorithms. They attained an F1 score of 0.71 and an RMSE of 4.21. Mishra et al. [15] focused on cancer classification using Machine learning techniques. Mishra et al. [20] focused on the classification of histopathological cancer images using deep learning models. S. Mishra et al. [31] focused on the skin cancer classification using CNN. They achieved the highest accuracy with the MobileNetv2 model. Mishra et al. [32] paid attention to the early detection of depression using various machine-learning techniques. The methodology is discussed in Section 3.

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Different machine learning algorithms used for classification are represented in Section 4. Section 5 deals with the experimental results and discussions. Lastly, the conclusion of the work is summarized in Section 6.

3. Methodology

This project focused on predicting depression from the collected data of patients. The classification was done using different machine learning algorithms, namely, Random Forest, K Nearest Neighbor, Decision Tree, Naïve Bayes, SVM (Linear and Polynomial), Logistic Regression, Extra Trees, XGBoost, Stochastic Gradient Descent, Grid Search CV, Stacking, and Voting Classifier. Figure 1 illustrates the block diagram of the work done in this paper.

3.1. The Dataset Description

The depression dataset used in this research was obtained from the Centers for Disease Control and Prevention. Data was filled by the participants using a questionnaire and comprised a variety of information, including demographic, medical (age and cancer), physical, and history of the patient. Birthplace, veteran status, and household income are considered in demographic data. Arthritis, body measures, blood pressure, cholesterol, alcohol consumption, sleep disorders, smoking, etc., are also taken into consideration as the parameters to measure the mental health of a patient. This data is released every two years [11]. The nature of the outcome variable is a Binary Class.

3.2. Data Pre-processing

It is pivotal for improving the accuracy of the prediction models. The following pre-processing techniques were applied to the data.

- **Feature Engineering:** Feature engineering involves transforming raw data into a format that improves a machine learning model's performance. It includes selecting relevant features, creating new ones, and optimizing existing ones to enhance the model's ability to learn patterns and make accurate predictions.
- **Filling missing values:** To emulate the way all information may not be available for every patient, missing values were filled as "missing" or 0. Instances where people refused to answer are treated as null values and filled with missing or 0. The null values are filled with empty strings across the rows to a single column to add all the values into one.
- **Scaling:** Scaling in machine learning refers to the process of standardizing or normalizing the features of a dataset. Scaling helps improve the convergence of optimization algorithms and enhances the model's performance.

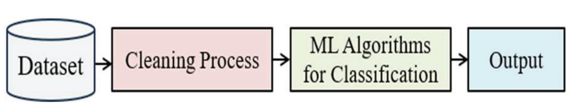

Figure 1.
Block diagram.

Table 1.

Details of the specification	
Model	**Specifications**
Used Software	Jupyter (6.5.2)
Language	Python
Kernel	Python 3.11.5 (ipykernel)
Library	Scikit-learn (version 1.3.2)
Framework	OSEMN
Number of Parameters Used	15

3.3. Model Training and Testing Strategy

The machine learning process begins with data collection and preprocessing, ensuring its quality and relevance. Next, a suitable model is selected, and a train-test split is applied. The model is trained on the depression dataset, adjusting its parameters to minimize errors and optimize performance. Different types of classifiers are used to make predictions. Finally, the trained model is deployed for making predictions or decisions in production environments. A model is trained and then fitted with various default parameters as a base. The dataset is divided into two subsets using a train-test split. The split is around 80% for training and 20% for testing. One-hot encoding is used for model preparation, especially as the dataset deals with categorical variables. One-hot encoding helps convert these categories into a numerical format that machine learning models can understand. The quantile transformer is used for scaling the data. K-means clustering is done on the data and added as a feature for modeling. For evaluating model performance, functions were written to run a classification report, make a confusion matrix, plot an ROC curve, and plot feature importance in the case of tree-based models. The specification chosen to perform experiments is shown in Table 1.

3.4. Proposed Model

Our proposed model is implemented in the following steps, as shown in Figure 2.

Step 1: The dataset is taken from the Centers for Disease Control and Prevention [11].

Step 2: Data Preprocessing begins by preparing the dataset, handling missing values, encoding categorical variables, and scaling features to ensure data quality and uniformity.

Step 3: Choose appropriate classifiers based on the problem's nature and data characteristics. Common choices include K-Nearest Neighbors (KNN), Random Forest, Naive Bayes, Decision Trees, and Support Vector Machines (SVM).

Step 4: The performance of the model is assessed using various evaluation metrics.

4. Classification Using ML Algorithms

Different classifiers, namely RF, KNN, NB, SVM, DT, ET, LR, XGB, SGD, LR Grid Search, Stacking, and Voting classifiers, were implemented for the classification of the dataset.

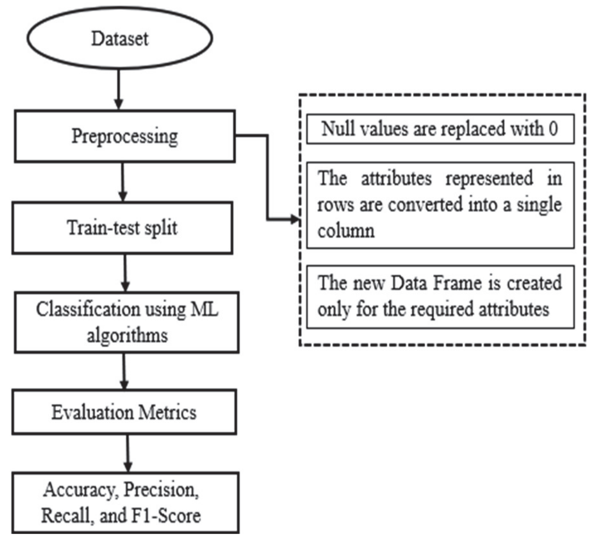

Figure 2.
Flow of implementation of our work.

4.1. Random Forest

RF creates multiple decision trees during training and combines their predictions for classification. Individual trees are trained on a random subset of the dataset. This reduces the overfitting of the data and increases accuracy.

4.2. K Nearest Neighbors

KNN assesses the labels of K-nearest neighbors in the training set. Widely used in supervised learning for pattern recognition, data mining, and intrusion detection. Choosing an odd K value helps avoid ties in classification, and cross-validation aids in determining the optimal K. Distance metrics like Euclidean, Manhattan, and Minkowski are employed to identify closest neighbors for query points that are written in Equations (1), (2), and (3).

$$\text{Euclidean distance } (x, X_i) = \sqrt{\sum_{j=1}^{d} (x_j - X_i)^2} \tag{1}$$

$$\text{Manhattan distance: } d(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{2}$$

$$\text{Minkowski Distance: } d(x, y) = \left(\sum_{i=1}^{n} (x_i - y_i)^p \right)^{\frac{1}{p}} \tag{3}$$

4.3. Support Vector Machine

The Support Vector Machine (SVM) identifies an optimal hyperplane in an N-dimensional space using the data points of different attributes. The hyperplane then maximizes the closest points of different attributes. Linear and Polynomial SVM were implemented in this project.

4.4. Stochastic Gradient Descent

Stochastic Gradient Descent (SGD) uses stochastic gradient descent optimization. SGD finds an optimal decision boundary by separating data points into different classes in a feature space.

4.5. Extreme Gradient Boosting

XGBoost uses gradient-boosted decision trees for classification. It works by combining predictions of individual trees and sequentially adding weak learners whilst correcting errors made by existing ones.

5. Results and Discussion

To measure the performance of the developed model, we consider accuracy (ACC), precision (Pre), recall (Rec), and F1-score metrics computed along with the confusion matrix, as shown in Figure 2. The following Equations (4), (5), (6), and (7) represent the formulations of the metrics. The confusion matrices and ROC curves of each algorithm was also plotted for evaluation of the performance of machine learning algorithms, as shown in Figures 2, 3, 4, and 5, respectively.

$$\text{Accuracy} = \frac{\text{Sum of diagonals (TP)}}{\text{Total number of instances}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{7}$$

Confusion Matrix – Figure 3 shows the confusion matrix drawn between actual and predicted classes. In this TP, FN, FP, and TN tell us about the True Positive, False Positive, and True Negative.

We obtained the following results for machine learning algorithms after performing our experiments on the depression dataset, as shown in Tables 2, 3, 4, and 5 for accuracy, precision, recall, and F1 Score, respectively. RF, KNN, SVM, XGB, SGD, Stacking, and Voting classifiers were applied, and their accuracies were compared. RF achieved an accuracy of 92% as compared to [12]. Polynomial SVM achieved an accuracy of 85% as compared to [14]. KNN

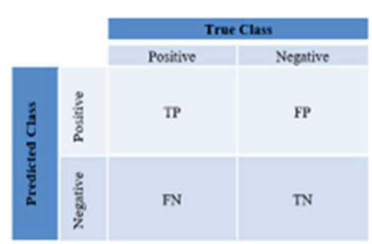

Figure 3.
Confusion matrix.

Table 2.

Accuracy comparison		
Classifiers	**References Accuracy %**	**Proposed Accuracy %**
Random Forest [12]	89	92
KNN [13]	84	86
Linear SVM [14]	85	92
Polynomial SVM [14]	85	85
XGBoost [12]	64	87
SGD	–	79

Table 3.

Precision comparison		
Classifiers	**References Precision %**	**Proposed Precision %**
Random Forest	–	92
KNN [13]	77	91
Linear SVM [14]	89	93
Polynomial SVM [14]	89	95
Decision Tree	–	91
XGBoost	–	94
SGD	–	96

Table 4.

Recall comparison		
Classifiers	**References Recall %**	**Proposed Recall %**
Random Forest	–	100
KNN	–	92
Linear SVM [14]	85	99
Polynomial SVM [14]	85	89
XGBoost	–	91
SGD	–	82

Table 5.

F1 Score comparison		
Classifiers	**References F1 Score %**	**Proposed F1 Score %**
Random Forest [12]	80	96
KNN [13]	77	92
Linear SVM [14]	85	96
Polynomial SVM [14]	85	92
XGBoost	–	93
SGD	–	88

achieved an accuracy of 86% as compared to [13]. We have also performed experiments using SGD. We achieved an accuracy of 79 % for SGD. We attained good precision in comparison to references [13, 14].

Table 3 shows that we achieved the highest precision of 0.96 with SGD. We achieved the highest recall value of 0.99 with linear

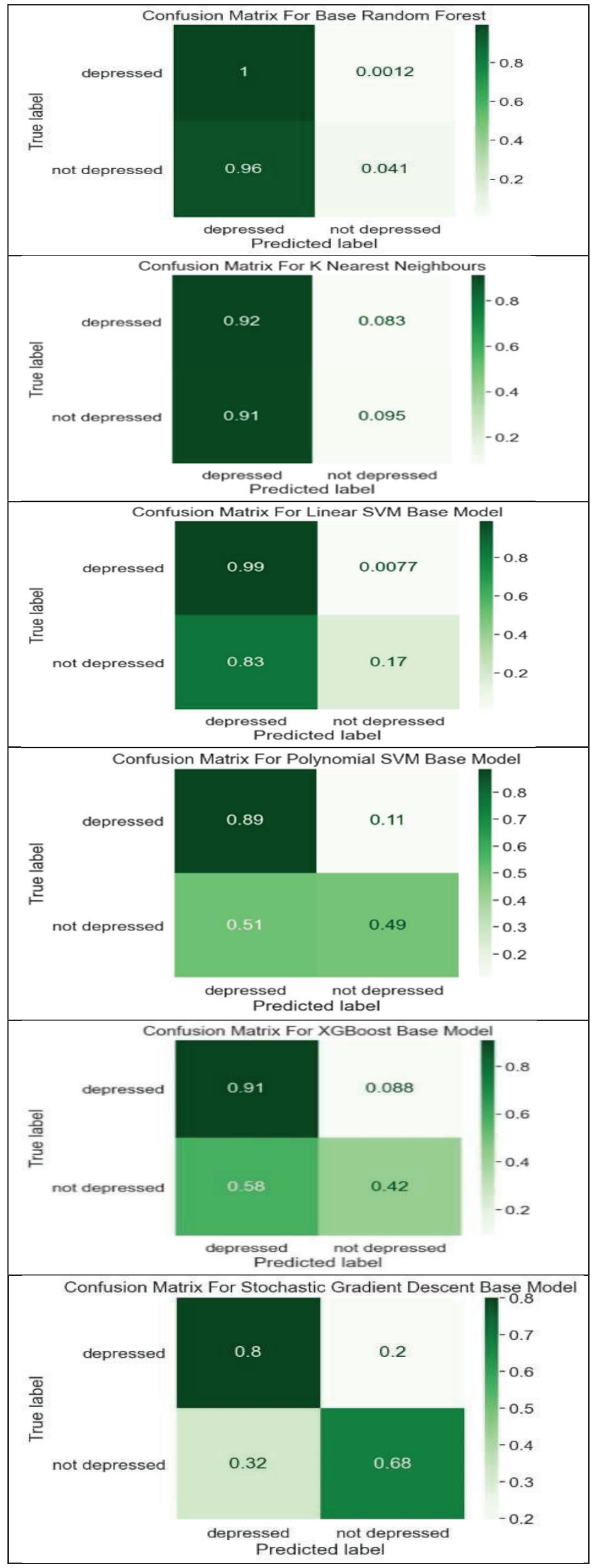

Figure 4.
Confusion matrix of RF, KNN, SVM, XGB, and SGD.

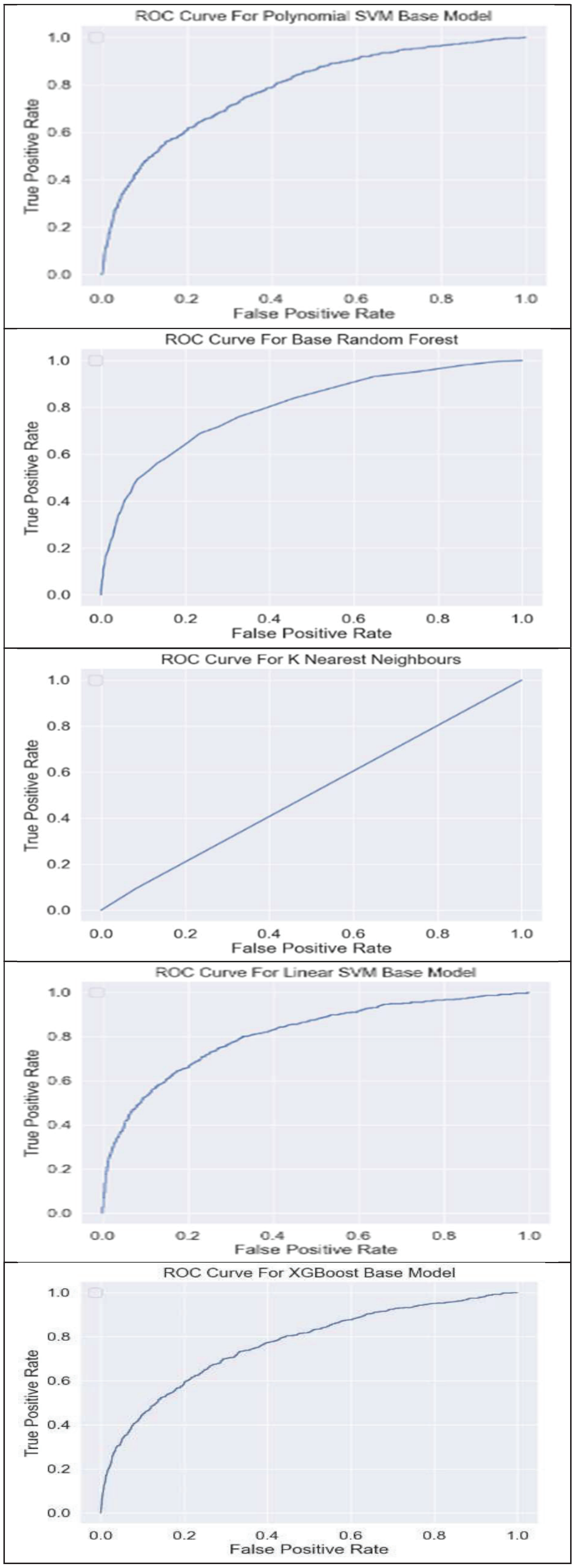

Figure 5.
Continued

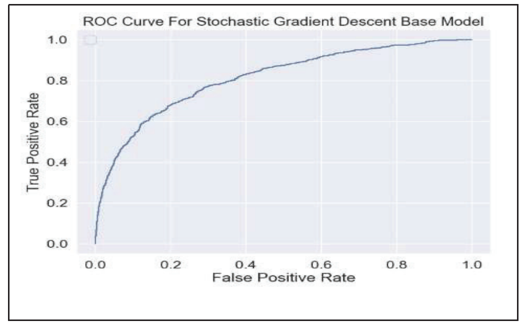

Figure 5.
ROC curves of RF, KNN, SVM, XGB, and SGD.

SVM, as shown in Table 4. We achieved the highest F1 score of recall value of 0.96 with random forest and linear SVM, as shown in Table 5. The performance of all the algorithms used can be compared using the normalized confusion matrices for binary classification and ROC curves, as shown in Figures 4 and 5, respectively.

It can be observed from Figure 4 that the base random forest correctly classified all depressed individuals as depressed (TP = 1), 96% of not depressed individuals were misclassified as depressed (FP = 0.96), and A very tiny fraction (0.12%) of truly depressed people were missed. Only 4.1% of not depressed people were correctly identified. We can understand it like this for the other models shown in Figure 4. Each point on the curve corresponds to a specific decision threshold, showing a combination of true positive rate (TPR) and false positive rate (FPR) values.

6. Conclusion

In this research work, different machine-learning algorithms were applied to the collected data. Random Forest outperformed other algorithms. We have achieved 3%, 6%, and 9% higher accuracy than [12–14]. We attained 0.99 precision using Linear SVM, which is better than [14]. Also, got a 0.96 F1 score higher than [12]. Depression continues to remain a life-degrading condition for millions. The application of machine learning can prove to be a transformative step in the healthcare industry. This work highlights the benefits of harnessing the potential of machine learning for mental health.

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Biographies

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4	Huddle 2025	September 23–24, 2025	Brasilia, Brazil	Sudhir Dixit/Vino Vinodrai/Hendrik Berndt	
5	WP5D	October 1–16, 2025	tbd	Nigel/BB/Vino	
6	WRC 2027	October 18–November 12, 2027	TBA	Nigel/BB	https://www.itu.int/en/ITU-R/conferences/wrc/Pages/default.aspx
7	WWRF56	October, 2026	Strathclyde University, Glasgow, UK	Nigel Jefferies/Hendrik Berndt/James Irvine	
8	WTDC	November 17–28, 2025	Bako, Azerbaijan	Nigel Jefferies/Bharat Bhatia/Vino Vinodrai	https://www.itu.int/itu-d/meetings/wtdc25/
9	WP5A & WP5C	November 17–28, 2025	Geneva	Bharat Bhatia/Vino Vinodrai	https://www.itu.int/en/ITU-R/study-groups/rsg5/rwp5c/Pages/default.aspx
10	WWRF54	November 4–6th 2025	Kingston University, London	Nigel Jefferies/Hendrik Berndt/Christos Politis	
11	IEEE Future Networks World Forum	November 10–12, 2025	Bangalore, India	Sudhir Dixit	https://fnwf2025.ieee.org/
12	IEEE Connecting the Unconnected (CTU) Summit	13-Nov-25	Bangalore, India	Sudhir Dixit	https://ctu.ieee.org/summit/2025-ctu-summit/
11	PP-26	November 9–27, 2026	Doha, Qatar	Nigel Jefferies/Bharat Bhatia	
12	6G Summit	November, 2025	Abu Dhabi	Lina Barriah	
13	SG5	Dec 1st 2025		Bharat Bhatia/Vino Vinodrai	
14	WWRF55	To be confirmed	Jaipur, India	Nigel Jefferies	www.wwrf.ch