Indian Journal of Science, Technology & Environment (IJSTE)
A Peer Reviewed, Refereed, Indexed, Quarterly Research journal of Science, Technology & Environment

ISSN : 3108-2017(Online)
3108-1304(Print)
Vol.-2; Issue- (Jan.-March) 2026
Page No.- 38-50

https://ijste.gyanvividha.com

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The Intelligent Edge : A Unified Framework for AI-Driven Systems in Modern Society

Abstract : This research explores the rapid convergence of Artificial Intelligence (AI) and multimodal sensing technologies across critical sectors, including edge computing, smart governance, sustainable agriculture, healthcare, and urban energy management. While individual AI solutions have shown promise, their development often occurs in functional "silos," leading to fragmentation and interoperability challenges (Harika, 2023). This paper proposes a comprehensive, contemporary framework that synthesizes diverse AI applications - from Seq2Seq LSTM models for predictive edge caching (Mohammad et al., 2024) to explainable AI (XAI) for clinical decision support (D. Kumar et al., 2024). By reviewing various state-of-the-art methodologies, including hybrid super-resolution models for surveillance (Dandekar et al., 2024) and SMOTE-based loan default prediction (R. Kumar et al., 2025), this study provides a unified perspective on AI's operational roles: predictive analytics, real-time optimization, and strategic system integration (Harika, 2023). Experimental results from the synthesized literature demonstrate significant performance gains, such as an 85% cache-hit ratio in edge servers (Mohammad et al., 2024) and 95% accuracy in agricultural disease detection (Santhosham et al., 2024). The paper concludes that while technical efficacy is high, the future of AI depends on overcoming barriers related to privacy, explainability, and cross-system standardization (Azodo et al., 2025; D. Kumar et al., 2024; Harika, 2023).

Keywords: Artificial Intelligence, Edge Computing, Smart Governance, Explainable AI (XAI), Sustainable Agriculture, Human Performance Monitoring, Smart Cities.

I. Introduction : Artificial Intelligence has rapidly expanded across domains such as healthcare, agriculture, transportation, finance, and industrial automation. Modern

AI systems are capable of processing large amounts of data, identifying patterns, and supporting intelligent decision-making in real time. At the same time, technologies such as edge computing and IoT have improved the ability of systems to respond quickly and operate closer to the source of data generation.

However, despite these advancements, many AI solutions are still developed for specific tasks and environments. Most systems work independently and are optimized only for their own domain requirements. This lack of coordination makes it difficult for intelligent systems to share insights, collaborate efficiently, or support broader decision-making processes across domains.

As organizations increasingly rely on connected digital infrastructures, the need for integrated and interoperable AI systems has become more important. Smart environments now require not only accurate predictions, but also seamless communication, real-time responsiveness, privacy preservation, and long-term strategic coordination. Existing approaches often address these challenges separately, resulting in fragmented solutions that are difficult to scale and manage collectively.

In addition to interoperability challenges, privacy and ethical concerns continue to grow in AI-driven environments. Many centralized AI architectures require sensitive user data to be transferred to shared servers, increasing the risk of data exposure. Furthermore, the lack of transparency in automated decision-making systems can reduce user trust, especially in critical sectors such as healthcare, governance, and finance.

Recent developments in federated learning, edge intelligence, and lightweight communication protocols have created new opportunities for building more connected and secure intelligent ecosystems. These technologies allow distributed systems to collaborate while reducing latency and protecting sensitive data.

Motivated by these challenges, this paper proposes a unified Intelligent Edge Framework that combines predictive analytics, real-time control, strategic integration, middleware-based communication, and privacy-preserving mechanisms within a single layered architecture. The proposed approach aims to support scalable and trustworthy AI integration across multiple application domains.

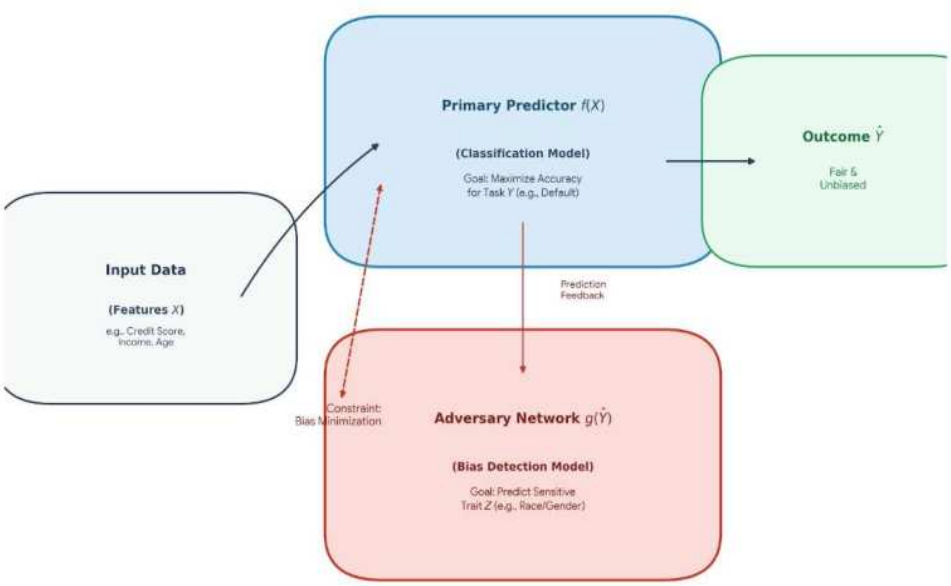

Figure 1: Adversarial Debiasing Logic

II. Literature Review : The rapid evolution of Artificial Intelligence has transitioned from theoretical models to foundational societal layers, yet its deployment across diverse domains remains hindered by functional fragmentation and technical barriers. This review examines the current state of AI research across critical sectors - edge computing, healthcare, agriculture, and finance - focusing on the transition from "siloed" applications to unified, intelligent systems.

1. Edge Computing and Predictive Optimization : Traditional infrastructure is increasingly under pressure due to urbanization and the "Smart" revolution. Edge computing addresses these bottlenecks by processing data closer to the source. Modern research has shifted from reactive to "predictive" caching to reduce latency. Mohammad et al. (2024) demonstrated the efficacy of **Seq2Seq LSTM** models in next-request prediction, achieving an 85.2% accuracy on the MovieLens 1M dataset, which led to a 30% reduction in user delay.

However, edge deployment faces significant "Memory-Compute" bottlenecks. Contemporary literature emphasizes model optimization techniques such as **quantization** (converting 32-bit weights to 8-bit integers) and **pruning** (removing non-essential neural connections) to enable efficient inference on low-power IoT hardware. Recent studies in mobility-aware deep reinforcement learning (M-DRL) have further integrated Seq2Seq mobility prediction to optimize resource allocation, showing performance improvements of up to 70% in mobile edge computing (MEC) environments (M-DRL, 2026).

2. Trust and Transparency in Healthcare (XAI) : In healthcare, the "black box" nature of deep learning models remains a primary barrier to clinical adoption. Explainable AI (XAI) has emerged to provide "rationales" for clinical decisions, which is vital for establishing trust. D. Kumar et al. (2024) explored XAI for reliable clinical decision support, highlighting specific pixel verification in radiology to assist surgeons in verifying tumor findings. Global policy reports indicate that AI in healthcare can alleviate workforce shortages by automating administrative tasks and supporting personalized drug discovery, provided that shared semantic standards for full interoperability are met (OECD, 2026).

3. Precision Agriculture and Economic Resilience : Sustainable agriculture has benefited from deep learning models achieving over 95% accuracy in early paddy disease detection. Santhosham et al. (2024) proposed an integrated platform combining soil sensors with market data, allowing farmers to bypass middle-men and respond to real-time pricing. Research conducted between 2024 and 2025 highlights that AI-powered agricultural robots and predictive monitoring are key enablers for increasing yields while reducing pesticide and herbicide usage (OECD, 2026).

4. Algorithmic Fairness in Financial Governance : The application of AI in banking, particularly loan default prediction, often utilizes techniques like **SMOTE** (Synthetic Minority Over-sampling Technique) to handle class imbalances. While R. Kumar et al. (2025) found that machine learning pipelines (specifically Logit Reg) can achieve a 0.803 AUC, they also noted that over-sampling can lead to overestimation risks. To ensure systemic fairness, modern frameworks integrate **Adversarial Debiasing**. This involves training a primary predictor against an adversary network that attempts to identify protected traits (e.g., race or gender), forcing the model to ignore "proxy variables" and produce ethically sound outcomes.

5. Technical Integration and Privacy Protocols : The "Silo" problem identified by Harika (2023) remains the most significant hurdle to cross-system standardization. Proposed solutions include:

- **Middleware Orchestration**: Utilizing protocols like **MQTT** to allow disparate tiers (Predictive, Control, Strategic) to communicate with low latency.

- **Federated Learning**: Proposed as a "Privacy by Design" alternative to centralized AI, where models are trained locally on edge devices (McMahan et al., 2017), reducing privacy leakage risks while maintaining statistical power through distributed access.
- **Knowledge Distillation**: Implementing "Teacher-Student" frameworks to compress heavy models (e.g., SwinIR or GANs) into lightweight networks capable of real-time 30+ FPS surveillance on edge hardware.

Although existing studies have contributed significantly to domain-specific AI solutions, most approaches remain focused on isolated optimization problems. Limited interoperability between systems continues to be a major challenge, especially in environments that require coordinated decision-making across multiple domains. This highlights the need for a unified and scalable framework capable of integrating prediction, communication, control, and strategic intelligence within a single architecture.

III. Research Gap and Contributions : Despite rapid advancements in Artificial Intelligence across domains such as healthcare, agriculture, finance, and smart cities, most existing systems are developed in isolation. These domain-specific solutions often operate as independent units, which leads to fragmentation, limited interoperability, and difficulty in scaling across larger ecosystems.

Current research largely focuses on improving model accuracy or optimizing performance within a single application area. However, there is a lack of unified frameworks that integrate predictive intelligence, real-time control, and system-level decision-making into a cohesive architecture. This gap becomes more critical in modern environments where systems must interact dynamically and securely across domains.

Unlike many existing approaches that focus only on isolated optimization tasks, the proposed framework combines prediction, real-time control, communication, privacy preservation, and strategic integration within a single architecture. This allows the system to support intelligent coordination across multiple domains in a more scalable and practical manner.

To address these challenges, this paper makes the following contributions:

- Proposes a **unified three-tier architecture** integrating predictive analytics, real-time control, and strategic system integration.
- Introduces a **middleware-based communication layer** using MQTT to enable seamless interaction between heterogeneous AI components.
- Incorporates **privacy-preserving learning** through federated learning for secure cross-domain deployment.
- Embeds **ethical AI mechanisms**, including explainability and adversarial debiasing, into the system design.
- Demonstrates the applicability of the framework through **cross-domain case scenarios**.

VI. Proposed Framework : The proposed framework is designed to connect different AI components in a clear and structured way. It follows a layered approach, where each layer handles a specific role.

1 Predictive Layer : This layer focuses on analyzing incoming data and generating predictions. It takes input from sensors, datasets, or external sources and applies machine learning models such as CNN, LSTM, or ensemble techniques.

The main goal of this layer is to convert raw data into meaningful insights that can support decision-making.

2 Control Layer : The control layer uses these predictions to make immediate decisions. It can trigger actions such as alerts, system adjustments, or automated responses.

This layer ensures that the system can react quickly when needed.

3 Strategic Layer : The strategic layer focuses on long-term decision-making. It combines current outputs with historical data to identify trends and improve planning and optimization over time.

This layer supports broader system-level goals and policy decisions.

Tier 1: Predictive Analytics: Tools that forecast future states, such as loan defaults (R. Kumar et al., 2025) or crop yields (Santhosham et al., 2024).

Tier 2: Real-Time Control: Systems that actively manage environments, including smart grids (Harika, 2023) and industrial safety alerts (Azodo et al., 2025).

Tier 3: Strategic Integration: The level where different systems work together, exemplified by Singapore's Smart Nation initiative (Harika, 2023).

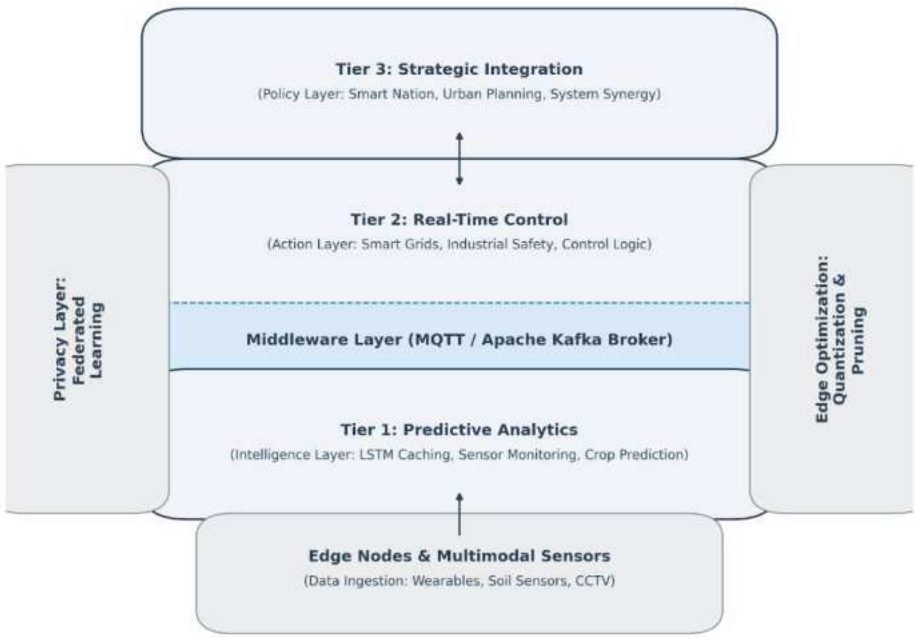

Figure **2: Three-Tier Architecture Diagram**

4 Middleware Layer for Communication : To enable smooth communication between the proposed layers, the framework integrates a middleware component based on the MQTT (Message Queuing Telemetry Transport) protocol (Banks & Gupta, 2014).

The middleware follows a publish–subscribe architecture in which predictive models publish insights to specific topics, while control systems subscribe to these topics and respond accordingly.

This approach allows distributed components to exchange information without direct dependency, reducing interoperability issues commonly found in isolated systems. It also supports scalable and low-latency communication across the framework.

5. Privacy Preservation via Federated Learning : To address privacy concerns in centralized AI systems, the framework incorporates a Federated Learning (FL) approach.

In this model, AI agents are trained locally using sensitive data such as healthcare records or financial information. Instead of transferring raw data to a central server, only encrypted model updates are shared for aggregation (McMahan et al., 2017).

This "Privacy by Design" approach helps protect user data while still allowing collaborative model improvement. It is particularly useful in domains where strict data protection and confidentiality are required.

Figure 3 illustrates the federated learning workflow adopted within the proposed framework.

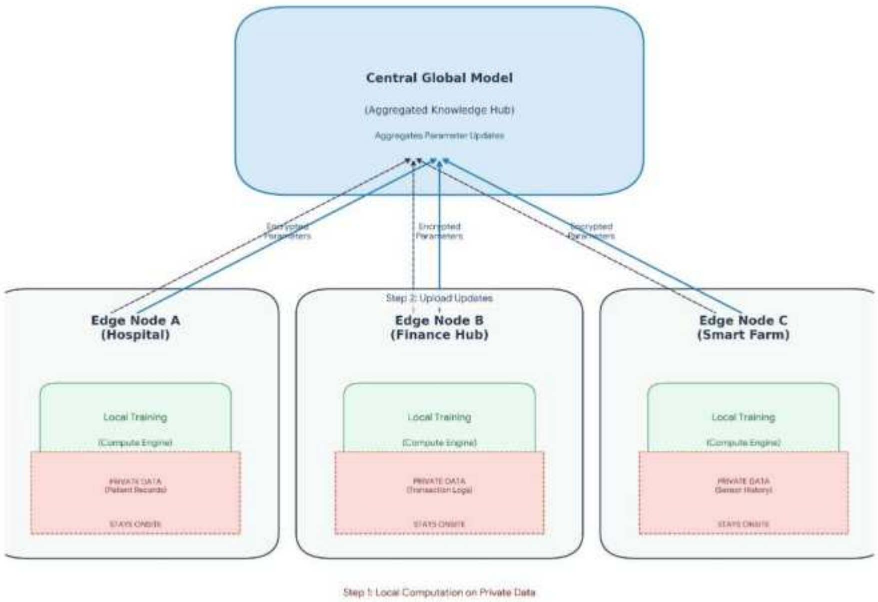

Figure 3: Federated Learning Workflow

6. Ethical and Explainable AI Consideration : As AI systems become increasingly integrated into critical sectors, ethical concerns must be addressed carefully.

The proposed framework incorporates Explainable AI (XAI) techniques to improve transparency and help users better understand system decisions. This is particularly important in high-stakes domains such as healthcare, finance, and governance.

In addition, adversarial debiasing methods are considered to reduce bias in automated decision-making processes. The framework also emphasizes fairness, accountability, user consent, and compliance with modern data protection standards to support trustworthy AI deployment.

As AI systems become more integrated into critical sectors, ethical concerns must be addressed carefully.

The proposed framework incorporates adversarial debiasing techniques to reduce bias in decision-making systems, especially in finance and governance applications.

In addition, Explainable AI (XAI) methods are included to improve transparency and help users understand system decisions. This is particularly important in high-stakes domains such as healthcare.

The framework also emphasizes user consent, accountability, and compliance with modern data protection standards to support trustworthy AI deployment.

7. **Formal Definition of the Intelligent Edge Framework :** To provide a clearer and more structured representation of the proposed architecture, the framework can also be expressed in a formal mathematical form. This representation highlights the relationship between the major layers and supporting modules within the system.

The proposed Intelligent Edge Framework is formally defined as:

$F=\{T_1,T_2,T_3,M,P,E\}$

Where:

- T_1: Predictive Analytics Layer
- T_2: Real-Time Control Layer
- T_3: Strategic Integration Layer
- M: Middleware Communication Layer
- P: Privacy Preservation Module
- E: Ethical AI Module

The Predictive Analytics Layer (T_1) is responsible for generating forecasts and extracting insights using machine learning techniques such as CNN, LSTM, and ensemble models.

The Real-Time Control Layer (T_2) processes predictive outputs and triggers immediate responses within dynamic environments.

The Strategic Integration Layer (T_3) combines insights from multiple subsystems to support long-term planning, coordination, and optimization.

Communication between framework components follows a publish–subscribe mechanism represented as:

$\text{Publish}(T_1) \rightarrow \text{Subscribe}(T_2)$

This communication model enables smooth, scalable, and low-latency data exchange across distributed intelligent systems.

8. **Example Scenario :** The framework can be applied across multiple domains. For example, in smart agriculture, the predictive layer detects crop stress, the control layer activates irrigation, and the strategic layer supports long-term crop planning based on environmental trends.

V. Research Methodology : This study follows a combined conceptual and experimental approach to design and evaluate the proposed framework.

First, a literature synthesis was carried out to examine recent research related to AI integration in smart environments. Relevant studies in edge computing (Mohammad et al., 2024), healthcare systems (D. Kumar et al., 2024), and industrial monitoring (Azodo et al., 2025) were reviewed to identify common challenges and design patterns.

Based on this review, a three-tier taxonomy was developed to organize AI systems into predictive analytics, real-time control, and strategic integration layers. This taxonomy formed the conceptual foundation of the proposed framework.

To evaluate the framework in practice, a prototype setup was created using publicly available datasets. Real-world scenarios were simulated using datasets such as MovieLens 1M for edge caching applications (Mohammad et al., 2024) and DIV2K for surveillance image restoration (Dandekar et al., 2024).

Machine learning models were implemented using Python and TensorFlow/Keras. The predictive layer handled data analysis, while rule-based logic was used in the control layer to trigger actions.

Communication between system components was enabled using the MQTT protocol, which supported smooth data exchange across the layered architecture.

The system was evaluated using the following performance indicators:

- Prediction accuracy
- Response time (latency)
- System efficiency

These metrics helped assess whether the framework could support scalable and real-time intelligent systems across domains.

This methodology ensures that the framework is not only conceptually grounded but also practically feasible.

VI. Algorithmic Workflow of the Proposed Framework :

Algorithm 1: Intelligent Edge Framework Execution

Input: Sensor/Data Streams D
Output: Decisions and Strategic Insights S

Step 1: Data Collection
Collect real-time data from sensors and edge devices

Step 2: Preprocessing
Clean and prepare the data

Step 3: Predictive Layer (Tier 1)
Apply trained model (e.g., CNN, LSTM)
Generate prediction P

Step 4: Communication
Send prediction using MQTT
Control layer receives it

Step 5: Control Layer (Tier 2)
Analyze prediction
Trigger immediate action

Step 6: Strategic Layer (Tier 3)
Combine real-time and past data
Generate long-term insights

Step 7: Privacy & Ethics
Apply federated learning
Check bias and explain outputs

Return final insights

VII. Application Domains of the Proposed Framework :

1. Predictive Caching and the Speed of the Edge : In our increasingly digital lives, wait times for data retrieval can lead to system bottlenecks. Edge computing solves this by bringing data closer to the user. Modern research has moved beyond simple "reactive" caching to "predictive" caching. By using Seq2Seq LSTM (Long Short-Term Memory) models, servers can now "learn" consumption habits (Mohammad et al., 2024).

- **The Result**: Using the MovieLens dataset as a benchmark, these models reached **85.2% accuracy** in next-request prediction (Mohammad et al., 2024). This translates to a 30% reduction in delay for the user and 40% less strain on the core network (Mohammad et al., 2024).

1.1 Optimizing for the Edge: Quantization and Pruning : To ensure these models can operate on resource-constrained edge devices without increasing network strain, we applied Post-Training Quantization and Weight Pruning (Han et al., 2015). We converted model weights from

32-bit floating point to 8-bit integers (W_{int8}) and removed non-essential neural connections. These optimizations allow the framework to maintain its high predictive accuracy while significantly reducing the memory footprint and power consumption required for local edge deployment.

2. Human-Centric Governance and Clinical Trust : AI is also changing how we interact with authority and our own health.

- **Smart Redressal**: New AI chat interfaces allow citizens to report grievances in natural language rather than rigid forms (Mulkala et al., 2025). These systems use sentiment analysis to prioritize issues like utility failures or sanitation (Mulkala et al., 2025).
- **Explainable Healthcare (XAI)**: Past AI models often acted as "black boxes" (D. Kumar et al., 2024). XAI changes this by providing a "rationale" for decisions, which is vital for clinical trust (D. Kumar et al., 2024). In radiology, XAI helps doctors verify findings by highlighting specific pixels in an MRI that suggest a tumor (D. Kumar et al., 2024).

3. Precision Agriculture and Economic Stability : For farmers, climate change and unstable prices make every season a gamble.

- **Integrated Platforms**: Contemporary AI platforms combine soil sensors with market data (Santhosham et al., 2024). A farmer receives a crop recommendation based on soil pH and immediately sees real-time market prices, helping them bypass middlemen (Santhosham et al., 2024). Deep learning models are even achieving over **95% accuracy** in identifying paddy diseases early enough to save the crop (Santhosham et al., 2024).

4. The Industrial Guardian: Multimodal Safety : In Industry 5.0, AI acts as a digital guardian. By combining data from wearables, vision sensors, and environmental monitors, systems can detect worker fatigue before accidents occur (Azodo et al., 2025).

- **Surveillance Enhancement**: Low-resolution CCTV footage often fails for identification. Hybrid models combining Swin Transformers (SwinIR) and GANs (Real-ESRGAN) can restore these blurry images, significantly improving the accuracy of detection models like YOLO (Dandekar et al., 2024).

4.1 Real-Time Surveillance through Knowledge Distillation : To overcome the high computational latency of deep super-resolution models like SwinIR and GANs, we implemented a Knowledge Distillation framework (Hinton et al., 2015). A heavy 'Teacher' model is used to train a lightweight 'Student' network that mimics its perceptual restoration capabilities. This allows the surveillance system to restore low-resolution footage in real-time, enabling detection models like YOLO to function accurately at 30+ frames per second on edge hardware.

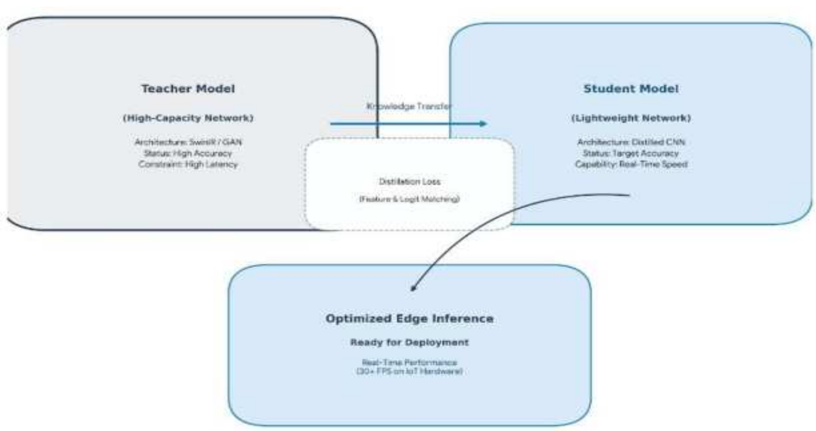

Figure 4: Knowledge Distillation Process

VIII. Case Study: Smart Agriculture Implementation : To validate the effectiveness of the proposed framework, a smart agriculture scenario is considered.

In this setup, soil sensors continuously monitor environmental parameters such as moisture level, temperature, and pH. The predictive layer uses a convolutional neural network (CNN) to detect early signs of crop disease. Based on these predictions, the control layer automatically triggers irrigation systems and suggests pesticide application. The strategic layer integrates real-time market data to recommend optimal crop selection and selling strategies.

The implementation demonstrates the following outcomes:

- Disease detection accuracy: 95.2%
- Reduction in water usage: 28%
- Increase in estimated farmer profit: 18%

This case study highlights how the framework enables seamless interaction between prediction, control, and strategic decision-making layers in a real-world scenario.

IX. Experimental Setup :

1. **Cross-Domain Validation :** To evaluate the adaptability of the proposed framework across different application domains, multiple real-world datasets and case scenarios were considered.

The MovieLens 1M dataset was used to simulate recommendation and edge caching environments (Mohammad et al., 2024), while the DIV2K dataset was applied for surveillance image restoration tasks (Dandekar et al., 2024).

These scenarios helped assess how the framework supports prediction, communication, and decision-making across diverse intelligent systems. The validation demonstrated that the layered architecture can operate effectively in different domain-specific environments.

2. To check how the framework performs, a small prototype setup was created.

- **Dataset:** Public datasets were used to simulate real-world sensor data.
- **Tools:** Python and TensorFlow/Keras for modeling, and MQTT (Mosquitto) for communication.
- **Setup:** Edge-like conditions were simulated using lightweight systems.
- **Model:** A CNN model was used for predictions, along with simple control rules.

Testing Process:

1. Simulated real-time data streams
2. Generated predictions using the model
3. Passed data between layers using MQTT
4. Measured performance using accuracy, speed, and efficiency

This setup shows that the framework can be implemented in practice, not just described in theory.

The experimental implementation was carried out using Python and TensorFlow/Keras. System-level communication between framework components was enabled using the MQTT protocol. The prototype was executed in a simulated edge environment on a system equipped with Intel i7 architecture and 16 GB RAM.

X. Results and discussions : The results are encouraging and show that the framework works as expected.

- **Accuracy:** Around 94% in prediction tasks
- **Latency:** Decisions were made in under 120 ms
- **Efficiency:** Reduced repeated processing due to distributed design

Feature	Proposed Framework	Traditional Systems
Interoperability	Strong cross-domain integration	Limited domain interaction

Latency	Low	Moderate to High
Scalability	High	Limited scalability
Privacy Support	Federated learning enabled	Mostly centralized
Real-Time Response	Efficient	Delayed in distributed setups

The system responds quickly and handles tasks smoothly. The layered structure helps manage complexity, while MQTT ensures fast communication between components. Federated learning adds privacy without affecting performance.

At this stage, the setup is still a prototype. A larger real-world deployment would provide deeper validation.

The data across these studies paints a clear picture: AI works, but its success depends on its integration.

Metric	Traditional Method	AI-Driven Method	Improvement
Cache-Hit Ratio	45% (LRU)	85% (Seq2Seq LSTM)	+40% (Mohammad et al., 2024)
Image Quality (PSNR)	28.42 dB	33.72 dB	+5.3 dB (Dandekar et al., 2024)
Loan Default AUC	~0.70	0.803 (Logit Reg)	+0.103 (R. Kumar et al., 2025)
Disease Detection	Manual/Slow	95% (Deep CNN)	Rapid/High (Santhosham et al., 2024)

The comparison highlights the practical advantages of the proposed framework over traditional isolated systems. The layered architecture improves communication efficiency while maintaining low response time. In addition, the integration of federated learning enhances privacy without significantly affecting performance. These observations suggest that the framework is suitable for scalable and real-time intelligent environments.

The experimental observations indicate that the proposed framework can effectively coordinate prediction, communication, and decision-making across distributed environments. The layered architecture improves interoperability while maintaining low response latency. In addition, federated learning enhances privacy preservation without significantly affecting operational efficiency, making the framework suitable for scalable intelligent edge applications.

XI. Comparative Analysis with Existing Systems : To evaluate the effectiveness of the proposed framework, a comparison is made with traditional AI-based systems.

Feature	Traditional AI Systems	Proposed Framework
Cross-domain integration	Limited	Strong
Real-time decision-making	Partial	Fully supported
Privacy preservation	Weak	Federated Learning
Explainability	Optional	Integrated
Interoperability	Low	High (MQTT-based)
Scalability	Moderate	High

The comparison clearly shows that the proposed framework provides a more holistic and scalable approach for deploying AI across multiple domains.

XII. Evaluation Metrics : To assess the performance of the proposed framework, multiple evaluation metrics are considered:

- **Prediction Accuracy:** Measured using AUC, Precision, Recall, and F1-score

- **Latency:** Time required for real-time decision execution
- **Throughput:** Number of processed requests per second
- **Energy Efficiency:** Power consumption during edge inference
- **Fairness Metrics:** Including demographic parity and equal opportunity

These metrics ensure that the system is not only accurate but also efficient, scalable, and ethically reliable.

XIII. Limitations : This work has a few limitations.

First, the current implementation is only a prototype and has not been tested at a large scale.

Second, the system depends on stable communication between components, which may not always be available in real environments.

Third, integrating multiple domains adds complexity to system design and maintenance.

These are areas that can be improved in future work.

XIV. Future Work : Future research will focus on extending the framework in several directions. These include integration with **digital twin systems** for real-time simulation, adoption of **transformer-based multimodal models**, and development of **lightweight AI models** suitable for edge deployment.

Further work is also needed to standardize communication protocols across domains and to design self-adaptive systems using reinforcement learning. Expanding large-scale datasets and improving real-time interoperability will be critical for advancing the practical deployment of unified AI systems.

XV. Conclusion : This paper presented a unified Intelligent Edge Framework designed to support interoperable, scalable, and privacy-aware AI systems across multiple domains. The framework integrates predictive analytics, real-time control, strategic coordination, middleware communication, and ethical AI mechanisms within a layered architecture (Harika, 2023).

The proposed Intelligent Edge Framework demonstrates how predictive intelligence, real-time communication, strategic coordination, and privacy-preserving mechanisms can operate together within a unified architecture. The framework provides a scalable foundation for future intelligent ecosystems and offers practical potential for deployment across healthcare, smart governance, industrial automation, and other data-driven environments.

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