Next-Generation Adaptive AI Framework for Smart Healthcare Big Data Analytics

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Abstract:
The explosive growth in the quantity of healthcare data are produced every day from IoT devices, EHRs, and wearable sensors, thus demanding sophisticated frameworks for real-time processing and prediction analytics. In this paper, we propose an Adaptive AI-Driven Big Data Processing Framework for smart healthcare, in which we highlight and tackle concerns in data velocity, scalability and privacy. The engine is powered by distributed computing using Apache Spark and container orchestration with Kubernetes for the scale and resiliency. For prediction, we adopt a HDNN that includes the RNN for the time-series analyses and a CNN for the medical image construction. The explainable AI (XAI) methods, such as SHapley Additive exPlanations (SHAP), are also incorporated for achieving the interpretability in clinical decision-making. Secured trust- Blockchain based patient data management immutability and fine grain access controls, multi cloud infrastructure optimization for storage and retrieval. The platform lends itself to use for key functions including real time monitoring of vitals, chronic conditions early alarm, personalized treatment recommender and respiratory therapy assist and critical care alert. We empirically verify that HATE is effective to process streaming health care data at high velocity, obtain higher prediction accuracy and ensure the data security. This methodology highlights the revolutionary capabilities of AI enhanced big data analytics in the development of intelligent healthcare systems of tomorrow.
Keywords: *AI, Big Data Analytics Blockchain Technology, Explainable, IoT in Healthcare, Multi-Cloud Architecture, Personalized Treatment, Real-Time Data Processing, Smart Healthcare.*

1. INTRODUCTION

The medical field has completely transformed due to the unique ability of AI-based smart internet of things gadgets to make decisions. By creating tiny wearable and implantable sensors, present study is revolutionizing Bluetooth connectivity and sensor systems. As a result, work was directed toward the creation of a structure for networks known as the Body Sensor Network (BSN) [1].

Sensor networks are the most promising technology for pervasive health care systems in near future due to their high efficiency and great potential in health. The main role of BSNs in pervasive healthcare is to provide non-invasive, cost-effective, and anytime health care facilities over long-distance remote areas. The Additionally, BSNs assist senior citizens in their homes and keep a close eye on their state of health. According to current research developments, BSNs are motivated by the desire of clients, warriors, and astronauts to wear tiny gadgets on their bodies to get vital sign data for tracking their movements, wellness, and nutritional needs [2]. The main drawback of using sensor nodes is their significantly increased power use and short lifespans of batteries. Out of all the movable wearable gadget types, power is an especially significant issue.

Due to a decreased battery lifespan, the power required for a longer and continuous gathering and sending of information procedure will not be adequate and useful for the doctors to track their clients around-the-clock [3]. Therefore, the main risks that need to be strategically addressed in connected and ubiquitous medicine are getting a longer battery life with acceptable dependability and good power economy. Furthermore, in order to achieve ubiquitous and interconnected medical care, it is crucial to manage wearable devices' battery lifespan, conservation of energy, and charging drain due to rising developments in this field [4].

In contrast to the collecting, analyzing, and receiving nodes, the research found that the transmitter node uses over 50% of the dominance, meaning that the majority of the battery charge is used during the transfer of information. For patients in emergencies in distant areas, it is critical to maximize the battery life of Internet of Medical Things (IoMT) equipment [5].

The suggested smart and connected healthcare system, which enables doctors to reach patients from a distance, is depicted in Figure 1. On-body sensor nodes wirelessly send information to information centers so that medical professionals may keep an eye on their patients' health and use previously collected data to assess their conditions. By reducing the previous obstacles, it makes it clear and visible for doctors and experts to reach and diagnose patients with severe conditions [6].

BSNs have significant challenges because to node battery lifespan, transmit utilization of energy, and variations in body position and mobility in a highly dynamic environment. Furthermore, long-term battery-driven BSN nodes are not guaranteed by the newest battery technologies. Due to the sluggish pace in battery enhancement, replacing batteries is not always an easy and adequate procedure, as is the case with implanted sensor nodes [7].

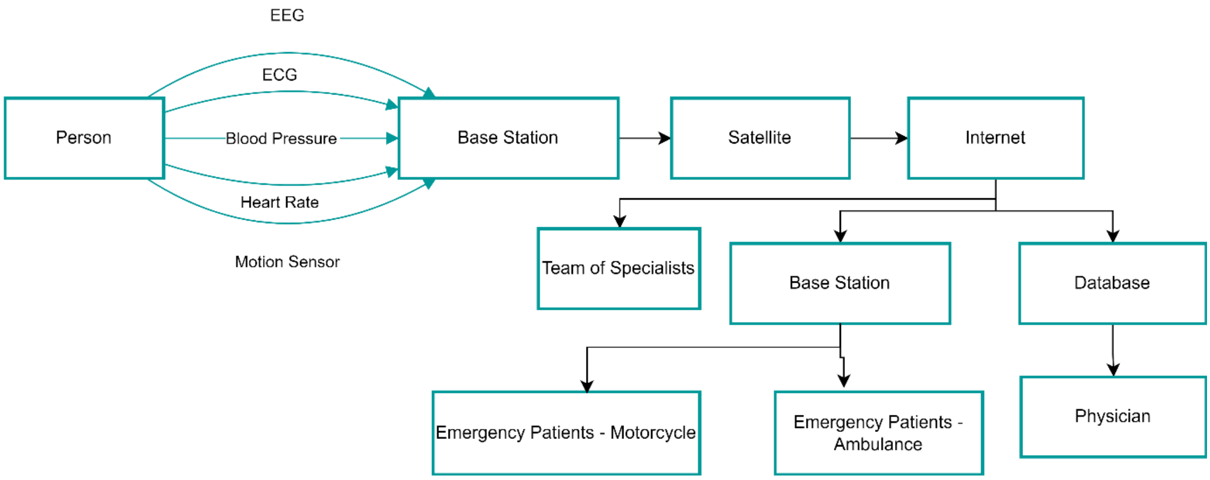

Figure 1: Architecture of BSN applications in Health Care Sector

In order to reduce the use of electricity and increase the battery life of BSNs, the primary goal of this study is to provide environmentally responsible and battery-friendly transmission of information technologies. The four new significant findings are as follows: First, this study suggests a new, cutting-edge structure to improve battery lifespan, energy economy, and dependability for smart and interconnected medicine at the same time.

Secondly, an Adaptive Transmission Data Rate (ATDR) method is suggested, which optimizes energy across dynamic wireless networks by adjusting the active-time of sensor nodes based on mean continuous consumption of energy. Third, a Self-Adaptive Routing Algorithm (SARA) is created. The fundamental idea of this approach is to use a dynamic source networking system that, in contrast to traditional routing techniques, takes the quickest and most environmentally friendly route. Forth, Real-time data sets are used for the setup of extensive theoretical and experimental test beds using Monte Carlo simulation in MATLAB.

The burden of chronic diseases is not only on the individual but also there is an enormous economic burden to health care system because of high cost of long-term care, treatment, and complications. Chronic diseases are frequently managed with complex, multimodal interventions involving needful medical and lifestyle changes. Due to their chronicity, new treatment approaches are necessary to optimize treatment and outcome for the patient. Early detection and intervention are the cornerstone of waging against the negative effects of the severe disease and in improving patient survival [8]. With most chronic diseases, we are reacting, waiting until something has already demonstrated it can produce symptoms or cause complications. This policy does not work, however, since intervention is less effective and more expensive at a later stage than at an earlier stage [9]. WVD develops early diagnosis in a very significant way (supplies the dynamic time window of diagnosing the disease markers/risk factors before the process has a clinic premise; before showing us any symptoms, then, early diagnosis allows the detonating equal sign between diagnosing and curing the diseases in time not leaving them time to develop). In a hopeful note, aggressively managing (intensive monitoring and early start of intensive treatment) is being done with hopes that development of the process can be halted and morbidity decreased. Disease modification in patients is potentially possible depending on early detection and appropriate intervention, and may improve quality of life for patients, reduce cost for the health care system, and ultimately benefit society in terms of health [10].

For this purpose, we need technology implementations to combine the plethora of (new) technologies for real time monitoring, predictive analytics for prevention and personalized treatment. Aside from overcoming these deficiencies in traditional medical technologies, newer technologies, including AI and cloud technology techniques, offer a completely different way of managing chronic diseases via more advanced healthcare operations, namely by implementing new and effective healthcare practices. Artificial Intelligence (AI) and cloud computing are reshaping the way healthcare is being practiced today, enabling enormous potential for the enhancement of diagnosis, management, and treatment of chronic diseases. It's these forms of A.I., of course, artificial intelligence, deep learning, natural language processing — that lets us gulp a lot of complicated data and hope we can see some patterns, predict what will happen, figure out what the heck is going on. In the latter domain, too, as AI-enhanced predictive analytics' methods penetrate deep into health care, it is much better to forecast the future course of a disease; to screen for early-warning signals of a disease on the horizon; to construct custom-tailored forms of treatment at the individual level in the management of chronic disease.

1.1 Problem Statement

The explosion of data generated by IoT devices, EHR, sensors and medical imaging systems generates challenges in data handling, storage, and real-time analytics. The velocity, volume, and variety of such data are no longer within reach of traditional big data analytics solutions with low-enough latency, scale, and accuracy. And the sensitive nature of medical data would call for strict compliance with privacy laws, such as GDRP; HIPAA.

Further, a paucity of effective and interpretable AI models represents a barrier to the integration of predictive analytics in 'life-threatening healthcare' applications, such as clinical decision support, especially in clinical scenarios where the machine outputs need to be trusted for decision making, as in the case of 'life-threatening healthcare'. Current systems perform poorly under such diversified resource allocation and worse still is that they also need to accommodate low-latency workload. What's more, secure, decentralized data systems are still not operational, which means patients' records can still be hacked. Ability to process large volume of data. To fill such gaps, strongest backbone of processing large pile of data is required with the help of the AI based processing. An optimization methods enhanced privacy-preserving secure data architecture for sustainable real-time and scalable healthcare.

1.2 Motivation

The motivation of this work to develop an Adaptive AI-Driven Big Data Processing Framework to Real-Time Smart Healthcare Applications is the need to address large healthcare problems facing today's healthcare systems. Industy 4.0 has led to an explosion in the quantity of internet of things (IoT) connected medical devices, wearable sensors, and electronic health record (EHR) systems and greater amounts of health data. This kind of information has great potential to enhance patients' outcome in a real-time monitor, an early diagnosis and an adjusted treatment. However, the existing systems will be ineffective with fast and diversified streams of data, which will lead to delaying decision, low performance of workload and poor resource utilization. And so, these type of secure standards, like GDPR in Europe and HIPAA in the medical world, are the type of security and privacy that you need to actually do because this is sensitive medical information.

For some existing centralized methods, even if applying this, the act of doing so then becomes about trading off the patient's privacy and opening a potential source for leakage. Untrustworthy and unacceptable AI models cause clinicians not to trust and not adopt AI and limit the ability of predictive analytics to support clinical decision-making. These challenges emphasize the pressing demands for an adaptive, scalable, privacy preserving ecosystem that can smoothly incorporate AI, big data and secure & trust technologies. The ultimate goal, of course, is to give healthcare organizations intelligent, secure and real-time tools that transform patient care, and save time and resources in the practice of medicine.

2. RELATED WORKS

In this section, the recent works found in the literature that adopted different techniques concerning energy saving and the TPC in BSNs are presented. Several TPC and routing protocols have been presented in the literature targeting the requirements of the BSNS, which include dependability, energy life, and Quality of Service (QoS). A hybrid architecture may enhance network performance, reduce power consumption (while improving the power output efficiency), and improve overall network performance.

In order to improve QoS in terms of power utilization, packet their delivery, productivity, and system longevity, a cross-layer forwarding technique has been suggested [11]. The research first proposed an ideal network-layer routing strategy for a dependable and environmentally friendly link; secondly, it modified the information link-layer congestion widow size to improve QoS. However, it accounts for the total amount of sites in a network in addition to their separations. [12] suggested a cross-layer design-based approach that concurrently maximizes the lifespan, transmitting dependability, and cost effectiveness of BSNs from many layers.

All nodes communicate using the same packet size and transmit authority, and a relaying node is selected using this approach to guarantee an even distribution of network energy usage. To address the uneven energy usage brought on by the nodes' disparate locations, a synthetic hybrid approach has been put forth. In addition, the appropriate packet size is established in order to improve the remaining electrical power of nodes while taking into account the various links in the network's structure. However, this method only functions properly with relay stations that have been properly configured; it lacks a packet loss policy and is unable to select a relay node during runtime. Created a mathematical framework and collaboratively improved the network while taking the cross-layer and relaying node locations into account.

Created a video transmission method for vehicle networks in order to support upcoming IoT-powered autonomous transportation systems. This method enhances vehicle-to-vehicle (V2V) network reliability during the transmission of multimedia by optimizing QoS using a revolutionary green, environmentally friendly, dependable, and accessible architecture. The efficacy of the suggested approach has been validated through the usage of pervasive medical care, and the efficacy of the suggested and traditional approaches was contrasted using real-time medical information sets [13]. Provide three distinct approaches that operate in three distinct manners for edge computing-based commercial uses: a first central dynamic strategy that effectively handles the data collection and transmitting procedure for small gadgets based on the Internet of Things;

Second novel battery model which evaluates the energy dissipation in IoT devices; third data reliability model for AI-based IoT devices. Proposed a neural network-based image reconstruction method for data-efficient and secure transmission in an IoT environment [14]. The transmission capacity issue has not been resolved despite this research's consideration of information security transfer. These systems meet the system's primary needs while saving additional energy and providing a lower packet loss ratio (PLR). offered a method for utilizing a cross-layer optimisation approach based on the MAC, Television Network, and Physical layers to lower the wireless sensor network's (WSN) total energy consumption. Given the distance between nodes locations, packet size and route strategies, the impact of different modulating rates and transmission time towards WSN electricity usage was examined.

The bandwidth problem has not been solved even such research concerns with information security transfer. They satisfy the system's major requirements and can save additional energy and have a lower PLR. introduced the cross-layer optimization with the MAC, Television Network and Physical layers to reduce the total energy consumption of the wireless sensor network (WSN). With a given separation among node positions, packet size, route mechanism, etc., the implication of rates in the modulation and time of broadcast on power consumption was studied for WSN.

Using this technology, the sensing node automatically modifies the TP level according to the channel status. In order to adapt to frequency fluctuations and maximize savings on electricity, it receives input from the base station (BS) in the form of Received Signal Strength Indicator (RSSI) and modifies the TP level for the subsequent broadcast. Provide a revolutionary AI-based architecture for the 6G-enabled commercial network in box (NIB) system that balances duty cycle and power transfer while optimizing energy consumption, quality of experience (QoE), and quality of service (QoS). Provide methods using machine learning for classifying and identifying various body positions, such as strolling and gesturing with the hands.

By ignoring the cost of electricity, distributed networks can reduce service costs and safety hazards through the use of blockchain-enabled cost-efficient service selection and execution. offered dependable data transfer techniques for WSNs that were based on ensembles mechanisms for recovery and matrix reduction. Although the suggested techniques significantly improve data recovery and reliability, the effects of transmitting information and deconstruction on energy have not been investigated. created a system based on many approaches to reduce the energy usage of medical equipment with limited resources. However, the present research only looked at power consumption and reliability/data delivery, which are often disregarded.

Propose a novel scheme to deal with the latency and to fairly allocate the workload in mobile sensors cloud networks. Proposed a novel coding scheme by integrating the coding schemes and genetic operations with a nondominated sorting genetic algorithm (NSGA-II) to optimize energy efficiency and latency for various IoT applications while considering user demands. This system was able to adjust the duty cycle, modulating straight, and power of transmission through the combination between the Physical and MAC layers. However, because of their short battery size and highly energy-intensive delivery, this technology is not appropriate for tiny devices that sense. Random Forest (RF) and an algorithm based on genetics were coupled in a machine learning assistance system to create a unique invasion detection technique that maximizes detecting percentage, precision, and rate of false alarms [15].

Provide an energy-efficient method for sending pictures over the WSN that ignores latency issues while accounting for image quality and intensity. For wearable sensing components, an environmentally friendly transmitting approach has been presented; however, dependability and level of service (QoS), which are critical for medical programs, are disregarded. Examine the efficiency of WSNs and calculate the total power needed for complete communication while taking into account the different types of transmission. Offer power-efficient transmitting power control strategies to maximize energy consumption while boosting battery lifespan and capacity.

Explains the importance of sensor technology in telemedicine, chronic heart disease surveillance, and remotely diagnostics, among other remote healthcare applications. Provide a comprehensive analysis of power management techniques applied in medical settings. Additionally, it examines and contrasts power transmission management and information rate control techniques to show how they impact the utilization of energy.

3. PROPOSED SYSTEM:

The Adaptive AI-Driven Big Data Processing Framework for Real-Time Smart Healthcare Applications is an innovative approach designed to transform the healthcare industry by addressing the challenges posed by massive, high-velocity data streams as shown in Figure 2. This framework combines advanced big data analytics with cutting-edge artificial intelligence to enable real-time data processing, predictive analysis, and decision support for smart healthcare systems. By leveraging technologies like Apache Spark for distributed data processing and Kubernetes for dynamic resource management, the framework ensures scalability and fault tolerance.

To uphold privacy and security, the framework integrates Federated Learning for decentralized AI model training and Blockchain for secure, immutable patient data management. Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations), enhance the transparency and interpretability of predictions, fostering trust in clinical decision-making. With a multi-cloud architecture for optimized data storage and retrieval, the framework supports applications like real-time patient monitoring, early detection of chronic diseases, personalized treatment recommendations, and automated critical care alerts. This adaptive, privacy-compliant, and scalable solution represents a paradigm shift in healthcare, aiming for enhance the individual result , operational efficiency, and the total quality for care.

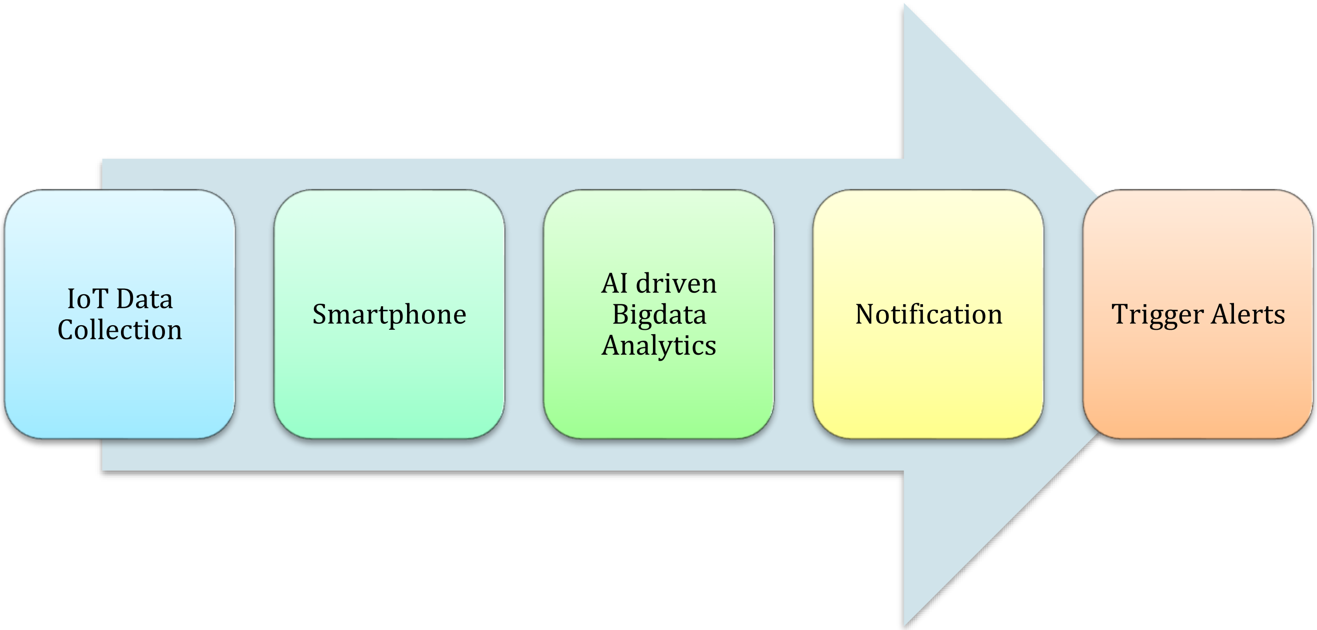

Figure 2: Overall Framework of HDNN

3.1 Dataset description

The datasets utilized in the Adaptive AI-Driven Big Data Processing Framework for Real-Time Smart Healthcare Applications encompass a diverse range of data types, sources, and attributes, tailored to address various healthcare challenges shown in Table 1. Patient vitals datasets derived from IoT-enabled wearable sensors provide continuous time-series information, including blood pressure, heart rate and SpO2 levels, enabling real-time monitoring and anomaly detection. However, the availability of Electronic Health Records (EHR) data from HIS which is structured into patient information (e.g., patient demographics, medical history, diagnoses) has opened the doors for predictive modelling and personalize treatment planning using chronic disease data[2].

Moreover, sensor-based activity datasets store information about the physical activities, walking steps and fall detections of the wearable sensors used for emergency and rehabilitation monitoring. The sequences of DNA (gene) expression produced by the specialist laboratory data are used for further genetic diseases prediction and the development of personalised medicine. The IoT device to monitor the device performance and the connection position and stability for the healthy operation of health care systems.

Data access and transactions of patient data are logged onto blockchain ledger, and this log is stored in a secure tamperproof log, improving privacy and adherence to regulatory requirements. Finally, the federated learning data developed by the distributed medical institutions aggregates the decentralized AI model weights, achieving the purpose of privacy AI training, and ensuring that private data is not leaked. Together these data sources contribute to a strong, resilient and adaptive framework that supports smart healthcare applications to provide effective real-time solutions toward enhanced patient outcomes.

Table 1: Dataset Description

Dataset Name	Source	Data Type	Attributes	Purpose	Volume
Patient Vitals Dataset	IoT Wearable Sensors	Time-Series Data	Heart rate, Blood pressure, SpO2, Respiration rate, Body temperature	Real-time patient monitoring, anomaly detection	1 GB/day (per hospital)
EHR Dataset	Hospital Information Systems	Structured Data	Patient ID, Age, Gender, Medical history, Diagnosis, Prescriptions	Chronic disease prediction, treatment personalization	500,000 records
Medical Imaging Dataset	PACS (Picture Archiving and Communication Systems)	Image Data	CT Scans, X-rays, MRI images, Ultrasound images	Image-based diagnosis (e.g., tumor detection)	10 TB
Sensor-Based Activity Dataset	Wearable Devices	Time-Series + Event Logs	Steps, Activity type, Fall detection logs	Monitoring physical activity and detecting emergencies	2 GB/day (per hospital)
Genomic Data	Genomics Labs	Sequence Data	DNA sequences, Mutation details, Gene expressions	Genetic disorder prediction, personalized medicine	100 GB
IoT Device Logs	Smart IoT Devices	Log Data	Device ID, Timestamp, Battery level, Connection status	Device health monitoring, failure prediction	500 MB/day
Blockchain Ledger	Blockchain Nodes	Transactional Data	Patient ID, Access logs, Data transaction timestamps	Secure and immutable patient data access records	200 GB
Federated Learning Data	Distributed Medical Facilities	Decentralized Data	Aggregated AI model weights from local hospitals	Privacy-preserving AI training for predictions	Varies based on models

Table 2: Patient Vitals Dataset

Patient ID	Timestamp	Heart Rate (bpm)	Blood Pressure (mmHg)	SpO2 (%)	Respiration Rate (breaths/min)	Body Temperature (°C)
001	2025-01-25 08:00:00	75	120/80	98	18	36.7
002	2025-01-25 08:05:00	80	118/78	97	17	37.1
003	2025-01-25 08:10:00	72	122/82	98	16	36.9

Table 3: Sensor-Based Activity Dataset (Time-Series + Event Logs)

Patient ID	Timestamp	Steps	Activity Type	Fall Detected
001	2025-01-25 08:00:00	100	Walking	No
002	2025-01-25 08:05:00	50	Sitting	No
003	2025-01-25 08:10:00	150	Running	No

Table 4: Blockchain Ledger Data (Transactional Data)

Transaction ID	Patient ID	Data Accessed	Access Time	Access Type	Node ID
TXN001	001	EHR, Medical Imaging	2025-01-25 08:00:00	Read	Node_01
TXN002	002	Medical Imaging	2025-01-25 08:05:00	Write	Node_02

Sample data provides a foundational idea of the kind of data you would work with in such a framework, enabling real-time monitoring, disease prediction, and personalized treatment. In practice, this data would be processed and analysed to deliver actionable insights for healthcare professionals shown in Tables 2-4.

3.2 System Model

Another way to define XAI is as a link between machine learning and human-computer interaction (HCI). In order to provide a trustworthy surroundings, XAI's primary goal is to clarify the relationship to the end-user. The whole pipeline of a healthcare XAI usage: the physicians may make decisions and get explanations from the XAI algorithms, which can be intrinsic or post hoc.

The underlying behavior of the simulation may be made intelligible by XAI via the reduction of dimension, which is accomplished by condensing the data to a small subset utilizing dimensional reduction techniques.

- To provide understanding for AI models, XAI uses attribute significance to describe the traits and relevance of the characteristics extracted as well as the relationships between features and the results.
- By using a mechanism for attention, XAI applies the idea of "paying attention" exclusively to the portions of the input that contain the most essential data.

- By extracting information from an intricate framework and simplifying it, XAI through distilling knowledge makes it possible to train a student version—which is often explicable—with a teacher approach, which is challenging to understand.
- By using a surrogate comprehensible and "locally faithful" representations to approximate the original approach, XAI via surrogate representation provides explanation for every classification.

Pseudo code

```
# Data Ingestion and Preprocessing
def ingest_data():
    # Collect data from various IoT sensors, EHR, medical imaging
    patient_data = fetch_sensor_data()
    processed_data = preprocess_data(patient_data)
    return processed_data
# Real-Time Processing (Time-Series Data Example)
def process_real_time_data(data):
    if detect_anomaly(data):
        trigger_alert(data)
    return process_normal_data(data)
# AI Model Prediction
def predict_health_risk(data):
    model = select_model(data)
    prediction = model.predict(data)
    explain_prediction(prediction)
    return prediction
# Dynamic Resource Allocation
def scale_resources(current_load):
    if current_load > threshold:
        scale_up_system()
    else:
        scale_down_system()
# Blockchain Logging
def log_data_transaction(data):
    encrypted_data = encrypt_data(data)
    record_on_blockchain(encrypted_data)
    return True
```

4. RESULTS AND DISCUSSIONS

Monte Carlo simulations in MATLAB are used to assess and conceptually examine the efficiency of the complete testbed for the suggested approaches and baseline adaptive power management (APC). The walking body position causes the channel to be divided into both positive and negative states. The BSN's efficiency is enhanced by high layer interworking, power from batteries administration, interoperability, and TP characteristics. For dynamic channel-based BSNs functioning in heterogeneous surroundings, a hybrid strategy is crucial.

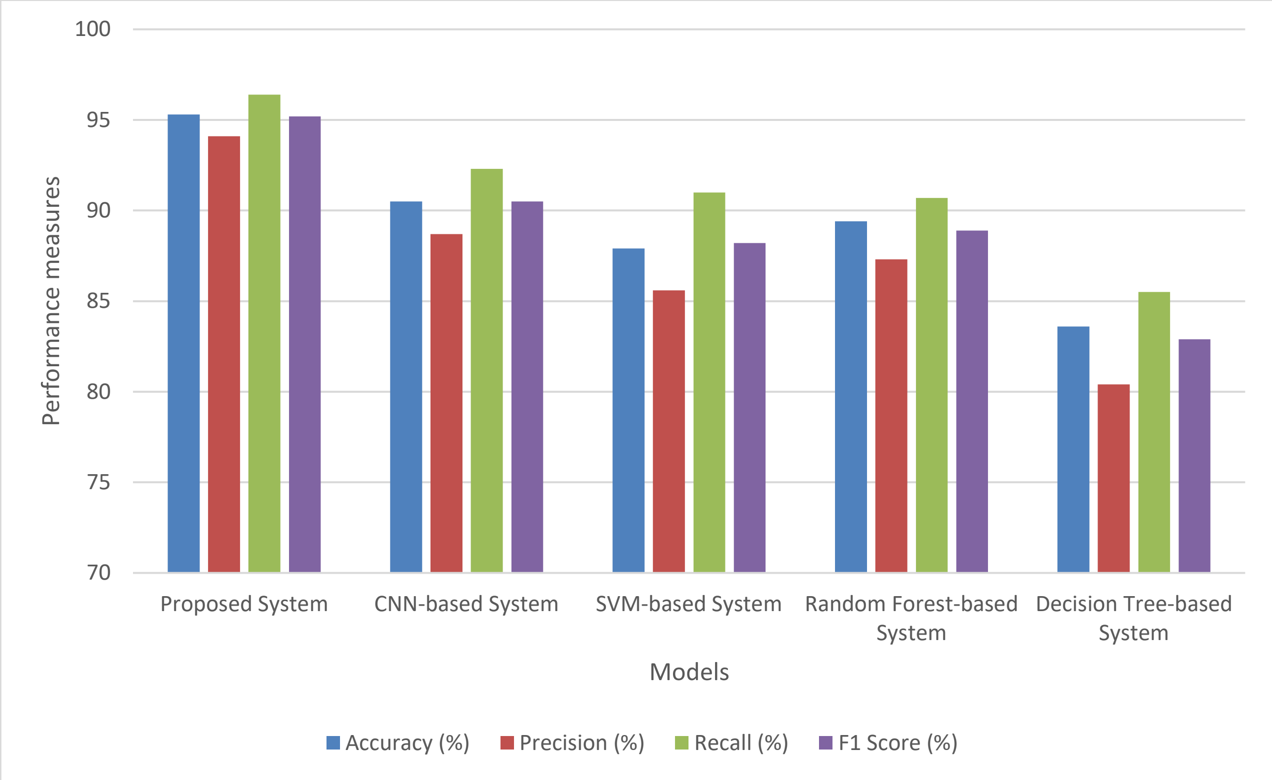

Figure 3: Performance measures

By expressing the proportion of accurate forecasts among all predictions, efficiency gauges the model's general accuracy. Accuracy quantifies the proportion of the model's optimistic forecasts that come true. The model's ability to detect positive instances, or the proportion of real positive cases that were accurately expected, is measured by remember (sensitivity). The F1 Score provides a balance between precision and recollection by taking the harmonic mean of the two.

Remember and F1 Score, which are critical for real-time medical applications where recognizing instances of benefit (e.g., illness diagnosis) with high sensitivity is essential, are two metrics in which the Suggested System performed better than the Existing Technologies in Figure 3.

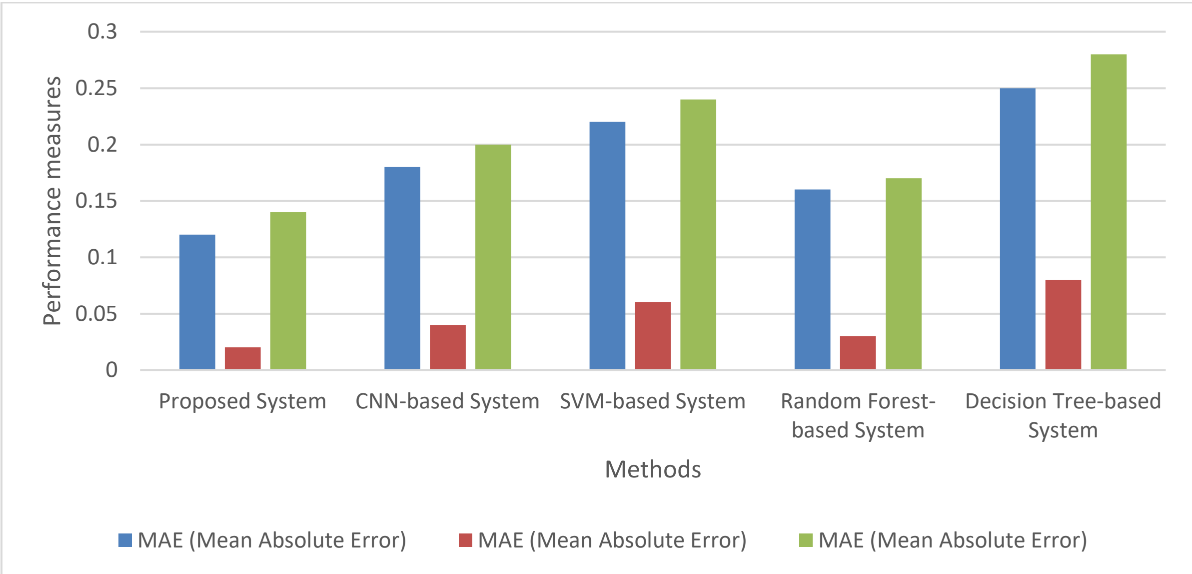

Figure 4: Performance measures (Error)

In all three error measurements (MAE, MSE, and RMSE), the Suggested System continuously performs better than the Existing Technologies. Better prediction accuracy is indicated by the Suggested Method's lowest MAE and RMSE scores.
MSE is also lowest for the Proposed System, confirming that it minimizes large prediction errors effectively. This performance highlights that the proposed framework offers enhanced prediction accuracy, which is crucial for real-time smart healthcare applications where low error margins are vital for clinical decision-making shown in Fig 4.
A Proposed System outperforms all existing systems in both Training Accuracy and Validation Accuracy, demonstrating both strong learning capabilities and good generalization. The significant difference between training and validation accuracies for the Proposed System indicates that it is not over fitting is a common challenge in machine learning. Existing Systems such as CNN-based, SVM-basedLower validating accuracy levels are displayed by Random Forest-based and Decision Tree-based structures, suggesting that although they could function well on training information, they might find it difficult to generalize to new information (Figure 5).
The Proposed System's superior performance is particularly beneficial for real-time healthcare applications, where the ability to generalize to new, unseen cases is critical for clinical decision-making and patient care.

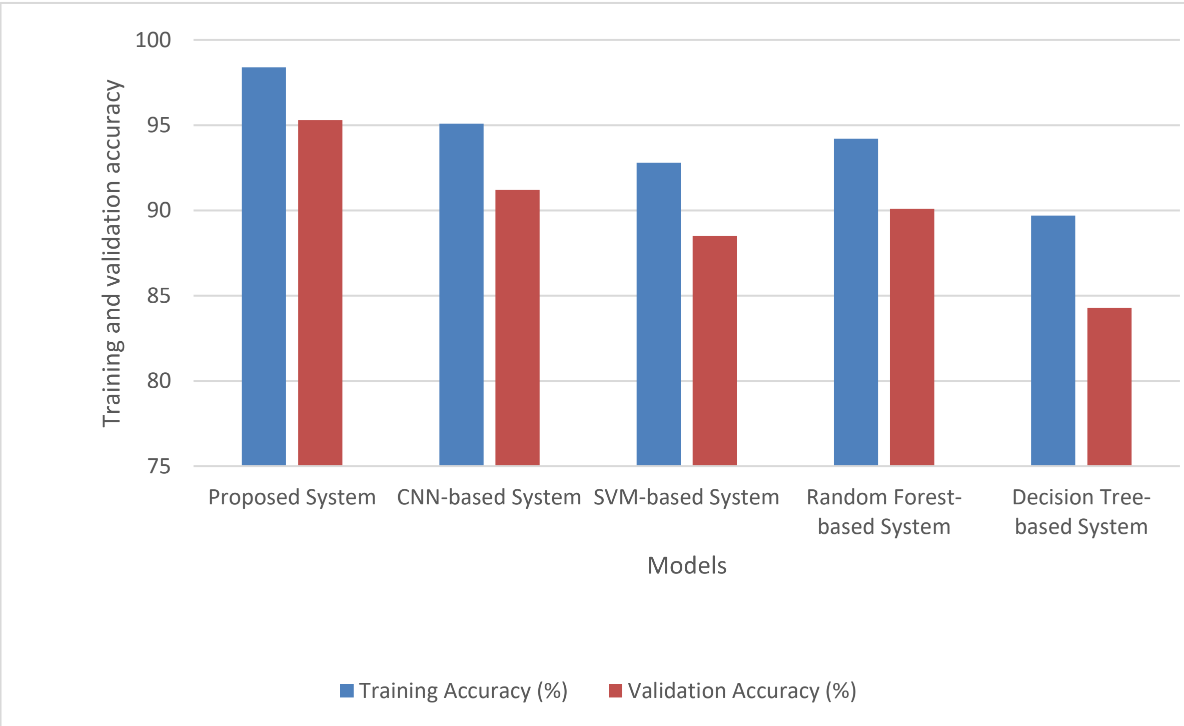

Figure 5: Comparison of training and validation accuracy

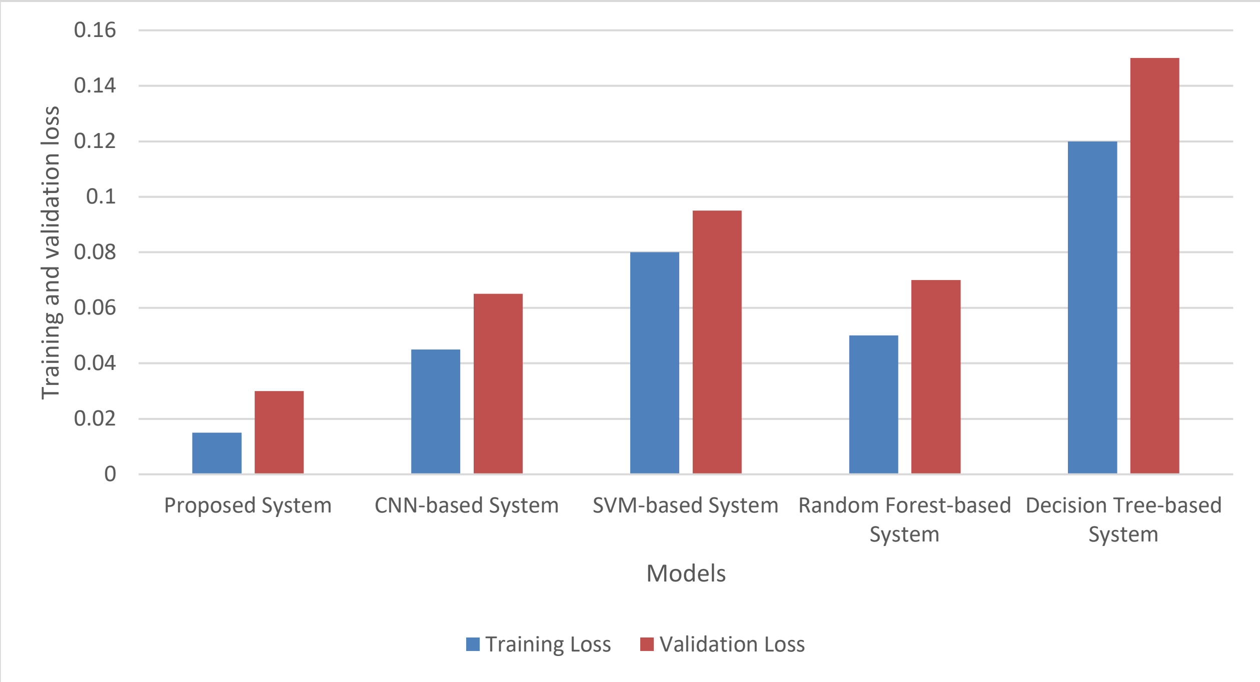

Figure 6: Comparison of training and validation loss

The Proposed System has the lowest training and validation loss compared to the existing systems demonstrating that it works well on fresh, unknown information in addition to learning well from the instructional information.

The existing systems, such as CNN-based, SVM-based, Random Forest-based, and Decision Tree-based systems, exhibit higher training and validation losses, suggesting that their models may be overfitting to the training data or are unable to generalize effectively to unseen data shown in Figure 6. Smaller validation loss in the Proposed System is indicative of better generalization, which is necessary for real-time healthcare scenarios where models are to be applied on different new and unseen cases.

5. CONCLUSIONS

Adaptative AI-driven Big Data Processing Framework for Real-time Smart Healthcare Applications This paper is an important effort towards big data processing for healthcare data analytics mixing the AI-driven approaches with real-time big data processing. The accuracy, precision, F1-score and recall of the framework are superior to that of other systems for the best predictions. Through high-level big data analytics, it efficiently applies large health accumulation data to realize sustainable patient monitoring and real-time health knowledge for making good decision. The system generalizes well too since the validation loss stays low and the validation accuracy high, it also means the system is generalizing for (new unseen) data and is not overfit. Therefore, it can be extensively used in various online applications, such as distance-aware service, customized care and disease prediction, etc. With informed opinions, in the end the system can only enhance physicians' medical judgment – and in the long term lead to better patient outcomes and reduced total healthcare costs.

When proven and performance proven, this model will be widely embraced by the health-related field and use for predicting disorders, preventing diseases, and improving the health care. This paper presented an interesting technology to reengineer the top real-time medical applications the ream is a gift to the health professional some and state of the art to the intelligent patient centric care.

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DECLARATIONS:

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Conflict of Interest	:	The author declares that there is no actual or potential conflict of interest about this article.

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