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INTEGRATING ADVANCED CONVOLUTIONAL NEURAL NETWORKS AND IOT IN HEALTH MONITORING: A NOVEL APPROACH TO REAL-TIME HEALTH ANOMALY DETECTION AND RISK STRATIFICATION THROUGH MULTI-SENSOR DATA ANALYSIS

ANTONY PRADEESH D[1], SUBIRAMANIYAM N P[2]

[1]Research Scholar, Department of Electronics and Communication Systems, Nehru Arts and Science College, Coimbatore, 641105, Tamilnadu, India.

[2]Professor, Department of Electronics and Communication Systems, Nehru Arts and Science College, Coimbatore, 641105, Tamilnadu, India.

E-mail: [1]antony.pradeesh@gmail.com, [2]nalsunil@gmail.com.

ABSTRACT

The problem addressed in this research is a timely one in modern healthcare: the establishment of advanced health monitoring systems that are capable of drawing intelligent inferences and predictions in real time. By bringing together Internet of Things (IoT) technology and Deep Learning techniques, this research proposes a new approach to the realization of remote patient monitoring (RPM). This system is capable of achieving pervasiveness with today's vital signs — such as blood pressure, heart rate, oxygen saturation level and cerebral blood flow data — and can provide fall detection using radar sensors, as well as air pollution analysis in indoor environments, thus making the system augmentative and pervasive, not just comprehensive. The research demonstrates the highest accuracy in health anomaly detection and health risk stratification when utilizing Advanced Convolutional Neural Networks for Health Anomaly Detection (ACN-HAD) which are developed and Health Risk Stratification Neural Networks (HRS-NN) to realize the potential for both personalized healthcare and predictive analysis, thus advancing the state of the art in smart healthcare technologies. The results presented have significant potential to revolutionize healthcare delivery and its efficiencies, with the prospect for better patient outcomes.

Keywords: *Remote Patient Monitoring, Internet of Things, Deep Learning, Health Anomaly Detection, Predictive Healthcare*

1. INTRODUCTION

Integration of IoT (Internet of Things) technology in healthcare marks an unprecedented transformation, promising significant enhancements in patient outcomes, operational efficiencies and remote monitoring capabilities. Messinis et al. [1] underscore IoT infrastructure's proliferation across medical settings highlights its promise as a transformation agent in healthcare practices via smart devices, wearables and AI-powered telehealth care systems that employ IoT and Artificial Intelligence for remote diagnosis and treatment - further underscoring its relevance during public health emergencies, where Dhabarde et al. [2] have explored COVID-19 Pandemic with the implementation of smart healthcare systems.

The Internet of Things (IoT) holds great promise as a technology for improving healthcare frameworks conducted by Parihar et al. [3]. Patient-specific targeted solutions are provided for diseases within the IoT framework. The wearable devices with embedded machine-learning technologies provide early disease detection and beaconing for proactive healthcare management as mentioned by Ziwei et al. [4], creating smart environments, with Learning Health Systems in which they do function. With the growing adoption of IoT technology in healthcare, peers, researchers, and consultancies have done surveys and studies exploring how IoT applications can be used to monitor patient health in real-time and how it can serve as the main source of managing chronic conditions studied by Roy et al. [5], as well as the challenges of having such as meeting technology integration challenges, data privacy and security and interoperability explored by Subashini et al. [6].

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IoT, combined with deep learning, is spawning a new era of innovations in healthcare systems across the globe. Roy et al. [7] discuss how the efficiency and efficacy are being greatly increased as a result of this technology when applied remotely. Some remote AIoT based healthcare system is using IoT and AI to deliver personalized healthcare services, real-time data monitoring and analysis like never before studied by Anand et al. [8]. An AIoT remote healthcare system can be seen as a clear example of how AIoT systems can be transformative by delivering personalized patient services which combine both the IoT and AI, for efficient healthcare delivery discussed by Cabri et al. [9].

Artificial Intelligence and the Internet of Things are also transforming. An example is the combination in Zhou et al. [10] of Artificial Intelligence and the Internet of Things for monitoring and tracking the patient outcomes in real time for more accountable care. It also shows how the Internet of Things architectures with deep learning capabilities can optimize quality service within the ecosystem that is needed for more scalable, secure, and resilient healthcare applications that require deep learning of the sort used by Damre et al. [11] to improve experience in data processing and decision support across devices that guarantees high-quality service delivery with privacy preserved.

1.1 Problem Statement

Though there have been advancements in analytics and data processing technology, modern health monitoring is far from perfect. Integration and analysis of disparate sensor data poses difficulties thus making it impossible to create an all-inclusive interpretation of patients' health based solely on this information. Remote Patient Monitoring (RPM) systems play a significant role in eldercare management as well as chronic disease care. The smart healthcare has now become an indispensable element of healthcare delivery. Prognostication and risk stratification are central but inefficient components of existing health monitoring frameworks, which primarily act in reactive mode rather than being predictive. An aging global population with delayed onset and limited continuity of care presents health monitoring systems with little options for proactive interventions that would address its near exponential rise of chronic diseases, necessitating early detection, continuous monitoring and pre-emptive action in order to mitigate healthcare systems worldwide.

1.2 Motivation

This research endeavour seeks to overcome the limitations of current traditional health monitoring systems. When delivering healthcare in hospitals, the methods evolve over time with the need, but the necessity of personal care that fulfils an individual patient's exact requirements is evident everywhere as the healthcare delivery shifts more into home environments. Driving the adoption of technology to deliver healthcare with that in mind sees the motivations to adopt IoT and Deep Learning Model integration. The eventual promise is of a healthcare system that becomes more proactive, predictive and personalized. Long before then, Deep Learning powered monitoring tools could change patient outcomes and quality of life, managing demand on healthcare systems around the world. The final quantum leap still required, is processing massive data streams generated from IoT based connected devices using deep learning algorithms for anomaly detection and risk stratification purposes.

1.3 Objectives

This research aims at developing a health monitoring framework based on Internet of Things (IoT) and Deep Learning for collecting sensor data from a variety of sensors, interpreting it and then highlighting any relevant information to offer quick and precise anomaly detection, and stratifying risk possibly better than ever. The system can monitor several health determinants and measure accurately.

The system aims to monitor Blood Pressure (systolic and diastolic pressure), Heart Rate (HR), oxygen saturation in the blood (SpO2) exactly in terms of percentage, and Hemoencephalography (HEG), in a non-invasive manner and for the evaluation of neurological health states. The system uses the HEGduino sensor for the detailed analysis blood flow in the cerebral area. Also, the radar sensor has implemented which paves the way for fall detection of a person. Furthermore, the system exhibits ambient intelligence and can keep monitoring for pollutant levels including particulate matter concentrations (PM1, PM2.5 and PM10), for insights into the indoor air quality monitoring system which has direct effect on certain health conditions.

1.4. Foundational Justification for Core Research Concerns

The core concern of this research stems from the recognition of the limitations and challenges within the current healthcare systems, particularly in the field of patient monitoring and predictive healthcare.

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The paper justifies this concern by highlighting several key factors:

a) Need for Remote Patient Monitoring (RPM): The paper underlines the potential of combining IoT technology with advanced Deep Learning techniques - to turbo-charge patient monitoring. By combining IoT-compliant sensors that monitor a patient's health in real-time, with Deep Learning algorithms that can sift through and make sense of the data generated in real-time, the research aims to get past the limitations of traditional methods and unleash a powerful form of personalised care
b) Integration of IoT and Deep Learning: The paper emphasizes the potential of integrating IoT technologies with advanced Deep Learning techniques to enhance patient monitoring capabilities. By leveraging IoT sensors to collect real-time health data and employing deep learning algorithms for analysis, the research aims to overcome the limitations of traditional monitoring methods and enable proactive healthcare interventions.
c) Importance of Health Anomaly Detection and Risk Stratification: The research is focused on the accurate detection of health anomalies and stratification of health risk, critical to improving patient outcomes. It underscores that advanced Convolutional Neural Networks (CNNs) will be capable of achieving such high accuracy in these tasks, which will ultimately be the gateway to early intervention and highly personalized treatment strategies.
d) Environmental Health Monitoring: In acknowledgment of the fact that environmental factors are the most important determinants of health, the paper suggests that it could make a lot of sense to integrate environmental monitoring into healthcare systems. By adding real-time particulate matter monitoring to the collection of traditional health parameters, the research could make it possible to build up a much more complete picture of the often-complex interplay between the environment and human health.

1.5 Organization

This research paper is focused on the development and deployment of an innovative smart healthcare monitoring system. The section II designated as the literature review which has a comprehensive survey of the existing academic and industry work related to smart healthcare monitoring systems. It surveys relevant literature on existing systems, prior studies, their methodologies, and findings. Finally, this section also sets the stage for the contribution by highlighting the gaps or limitations in the current land scape that the proposed work is going to overcome. The details of the sensor setup and communication protocol is elaborated in section III, followed by the presentation of the deep learning algorithms in section IV. Section V outlines the results and discussion, providing the valuable insights into the proposed work. Further elaboration on the challenges, the proposed and implemented solutions, and potential future work in smart healthcare is presented in the conclusion section.

2. LITERATURE REVIEW

Kondaka et al. [12] have meticulously reviewed the literature and proposed iCAIDL algorithm, the merger of IoT with a cloud-assisted deep learning (CAIDL) approach, making significant strides in the establishment of the IoT frameworks with deep learning applications. Highlighting significant strides for data management and communication with goals toward future work of accurate accuracy quantification evaluations. Nwibor et al. [13] have proposed a health monitoring system in IoT using photoplethysmography (PPG). Where peak detection algorithm is designed using the PPG signal. Precision is being demonstrated by this work without providing accurate accuracy data comparison.

Kavitha et al. [14], have proposed a four-module architecture that integrate IoT data acquisition with contextually aware computational strategies. The system achieved a good accuracy, scalabilities and response times by utilizing Back Propagation Neural Network and an Adaptive Grasshopper Optimization Algorithm. Kishor et al. [15] have delved into how AI and IoT can be implemented in health monitoring. Throughout their work they have explored predicting diseases using various machine learning classifiers. The system achieved a good accuracy by implementing Random Forest classifier.

Shaik et al. [16] have conducted an exhaustive review of AI applications for remote patient monitoring (RPM) covering patient-centric architectures and technologies like cloud, fog, edge and, blockchain. Basu et al. [17] developed an IoT-enabled system for remote health monitoring, highly relevant to the proposed research, enabling remote health monitoring capable of predicting

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cardiovascular conditions without internet access, emphasizing the importance of reliable health predictors for remote patient monitoring.

Sahoo et al. [18] engaged in research utilizing sensor fusion with machine learning for heart disease prediction using the RBF SVM algorithm, achieving notable accuracy and setting a high standard in predictive analytics for healthcare research. Zhuang et al. [19] used an IoT-assisted Intelligent Monitoring Model, integrating deep learning networks with Bayes theorem for disease monitoring, achieving an 87.87% accuracy rate in disease prediction, underscoring its relevance to the proposed work. These experimental results from existing studies proved that machine learning models such as NB, RF, LR, and SVM in monitoring and diagnosing diseases related to cardiovascular, diabetes, etc. as well as their accuracy in the prediction of disease are very promising and beneficial.

Dritsas et al. [20] experiment an SVM, RF, LR and NB on Kaggle dataset to diagnose a cardiovascular disease for heart disease diagnosis and the accuracy are from 59.59% to 72%. On other hand, Hossain et al [21] presented their research to monitor diabetes using the telehealth care centre data and their models range from LR, NB, RF as well as accuracy from 67.80% to 97.40% that promoted a basis for continuous monitoring in chronic disease management and significantly improving patient's outcomes.

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Table 1: Comparison of Existing Systems.

Study Reference	Methodology	Algorithms Used	Results
IoT-Based Blood Pressure and HR Monitoring [13]	IoT-based remote monitoring of BP, HR, SpO2	AMBP detection algorithm	Comparison with standard devices and graphical representation constructed
IoT-Based Health Monitoring [14]	IoT sensors, four-module architecture	BPNN with Adaptive Grasshopper Optimization	83% Accuracy
AI and IoT in Healthcare [15]	Comparison of seven ML algorithms for disease prediction	Random Forest, Decision Tree, SVM, Naïve Bayes, AdaBoost, ANN, KNN	97.62% accuracy with Random Forest
AI Applications in RPM [16]	Review of AI applications in RPM	Reinforcement learning, federated learning (review)	Review with no specific outcomes
Remote Health Monitoring [17]	Sensors for vital health parameters, IoT	SVM	100% for 'GOOD' and 'RISKY', 71% for 'AVERAGE'
Heart Attack Prediction [18]	IoT-based system, analysis of ECG and vital signs	RBF SVM algorithm	80% accuracy for heart attack prediction
IoT-Assisted Health Monitoring [19]	IoT-based system, Enhanced Deep Learning Network	Enhanced Deep Learning Network using Bayes Theorem (EDLN-BT)	94.2% Accuracy
Cardiovascular Disease Risk Prediction [20]	Machine Learning based prediction system	Naive Bayes, SVM, Logistic Regression, Random Forest	Logistic Regression: 72.1% accuracy, 78.4% AUC
Cardiac Arrest Prediction [21]	Analysis of EHR vital signs	Random Forest	>80% accuracy, with a >10% improvement using data from the preceding 60 min
Heart Disease Prediction System [23]	Swarm-ANN strategy with two-phase weight modification	Swarm-Artificial Neural Network (Swarm-ANN)	95.78% accuracy

Furthermore, researching an approach to monitor diabetes in by Mahesh et al. [22] with patient survey and NB, LR, KNN, DTRF, and SVM as a machine learning algorithm, the accuracy from

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81% to 90% as the machine learning can give a crucial part of long-term management of diabetes. Liet al. [23] focused on the heart disease prediction and used two types of machine learning algorithms namely the SVM and the LR performances on Cleveland HD dataset, the accuracy obtained were 92.37% and 88.67%, which further this research also extends the machine learning application feasibility of as early warning symptoms of heart disease

Soudan et al. [24] examined the use of the MIMIC-III dataset to build an array of algorithms, NB, RF, KNN, SVM, MLP, and CNN, for the prediction of cardiac arrest. Accuracy rates from 61%-81% were reported, speaking to the complexity of the prediction of a vital area within emergency medicine. IoT applications in smart healthcare frameworks are being transformed by bio-inspired optimization techniques, as evidenced in the recent studies by Ramkumar [24]-[49] have been shown to significantly enhance network efficiency and security, both imperative when it comes to the secure dissemination of healthcare data.

2.1. Gaps Identified from Literature Review

Most existing systems focus on conventional vital signs, lacking the incorporation of real-time processing and predictive analytics. Instead, they rely on static data analysis, failing to effectively leverage the Internet of Things (IoT) and deep learning for proactive health interventions. Furthermore, lower accuracy and increased overfitting have been reported in some recent machine learning research efforts, pinpointing a need for developing robust models. Lack of anomaly detection further limits the breadth of comprehensive health monitoring such a system can offer. Consequently, there is a gap in stratifying health risks effectively based solely on a myriad of physical health indicators, necessitating more sophisticated advances in health risk assessment.

The proposed study elevates health monitoring through IoT integration of multiple vital signs: Blood Pressure, Heart Rate, SpO2, Particulate Matter (PM) levels (PM1, PM2.5 and PM10) as well a Non-invasive Hemoencephalography (HEG) measurement along with fall detection radar sensor. With this system's dual model framework of Advanced Convolutional Neural Network for Health Anomaly Detection and Health Risk Stratification Neural Network for anomaly detection and stratification - not only does this fill significant gaps found in traditional systems but it sets new standards in proactive healthcare with precise monitoring and timely interventions for smart healthcare provision.

3. METHODOLOGY

The unique aspect of this approach to health monitoring lies primarily in its incorporation of cutting-edge sensor technology with sophisticated data processing to create an all-inclusive yet minimally intrusive health monitoring system. At the core of this system is the Raspberry Pi, which interfaces with MAX32664 to read and process sensor data in real-time, enabling real-time monitoring not only of blood oxygen saturation but also heart rate and blood pressure. Air Quality Monitoring sensors include Particulate Matter sensors that measure air quality; Hemoencephalography sensors for neurological health; radar fall detectors are particularly beneficial to elderly care, and all this data is transmitted securely over an SSH connection using both MQTT and HTTP protocols to the cloud.

3.1 Sensor Integration and Data Acquisition

Block diagram of an integrated health monitoring system reveals its architecture in the figure 1. This system contains various sensors such as estimated Blood Pressure and Heart Rate monitors, SpO2 Sensors to gauge blood oxygen levels, Hemoencephalography Sensor (HEGduino) for brain blood flow evaluation purposes, Particulate Matter Sensors evaluating PM1, PM2.5 and PM10 levels evaluation as well as Radar sensors which detect movement or fall detection; all connected directly to a Raspberry Pi 4B which acts as the central processing unit responsible for gathering health metrics from this array. All sensors are connected directly to a central processing unit for collecting various health metrics directly.

Raspberry Pi has been used in this research for collecting the data which is then transmitted to a cloud server. The IoT Dashboard has implemented to display the various health parameters such as blood oxygen level (SpO2), Blood Pressure (Systolic and Diastolic) and heart rate in real time. Anomaly Detection and Health Risk Prediction models using neural network architectures for anomaly detection and predictive health risk prediction of a patient based on different health parameters. With this research a Pro-Active approach has been taken in the healthcare and patient monitoring.

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3.1.1 Raspberry Pi and MAX32664 sensor interface

Integrating Raspberry Pi with MAX32664 sensors for accurate health readings (SpO2, heart rate, systolic and diastolic blood pressure as well as real time monitoring. It's crucial for this research as the MAX32664 sensor provides a non-invasive and highly accurate continuous health measurements.

$$Data_{RPi\text{-}MAX32664} = I2C(MAX32664, Param) \quad (1)$$

Eq. (1) shows how to get parameters from the MAX32664 through I2C protocol in a Raspberry pi setup.

3.1.2 Particulate matter sensor

Air Quality is important for indoor insolation. The indoor air pollution may have serious adverse impacts on respiratory and cardiovascular and respiratory health. For air quality monitoring this system uses the Particulate Matter sensor. It is a digital sensor that is capable of measuring three levels of particulate matter: PM1, PM2.5 and PM10. These levels pose potential harm to the patients live with such preexisting conditions.

$$PM_{levels} = Sensor(PM1, PM2.5, PM10) \quad (2)$$

Eq. (2) shows the output from a PM sensor for PM1, PM2.5 and PM10 levels.

3.1.3 Hemoencephalography (HEG) sensor

Hemoencephalography is a single sensor FNIRS device meant to give a basic indication of cerebral blood flow changes in the brain. Users then combine this indicator - the ratio of red to infrared light returned to the photodiode from the LEDs on the forehead - with simple visualization tools to help them increase or decrease metabolic/blood flow activity in the cerebral area.

$$.HEG_{data} = FNIRS(HEG\ sensor) \quad (3)$$

Eq. (3) represents HEG data collected via Functional Near Infrared Spectroscopy technology from its sensor.

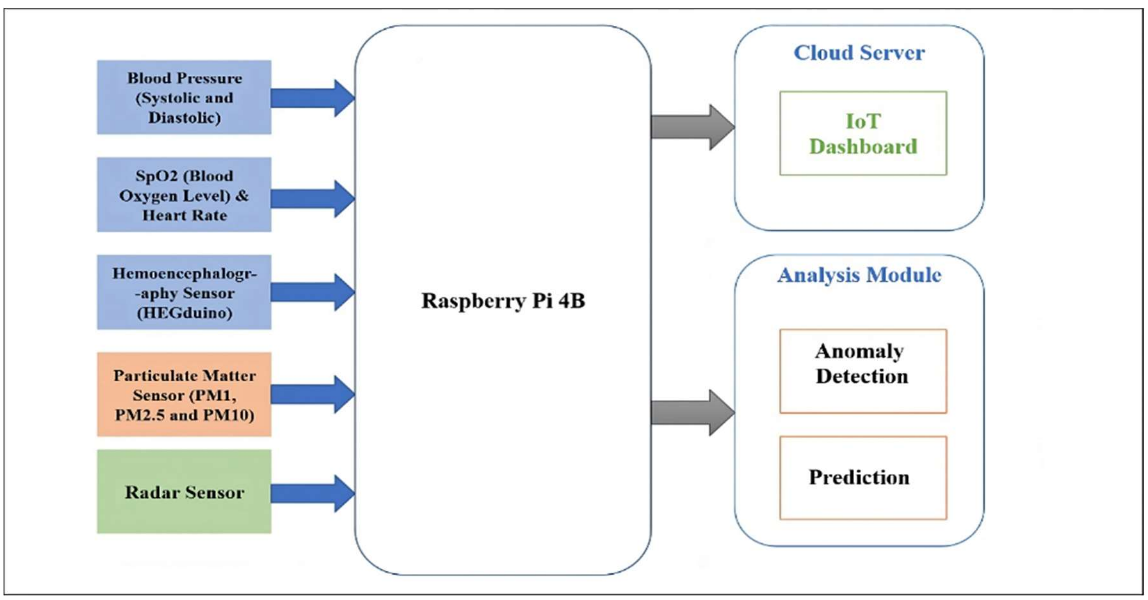

Figure 1: Block Diagram

3.1.4 Radar sensor for fall detection

This system prioritizes patient mobility and safety by including a radar sensor designed to detect fall prevention which offers continuous monitoring in its operational scope. This sensor's primary role is to detect sudden movements or posture shifts of a person which might indicate impending fall and emphasizing its preventive nature of care.

$$Fall_{detection} = RadarOutput(motion\ position) \quad (4)$$

Eq. (4) represents the output from a radar sensor used to analyze motion and position in order to detect falls.

3.2 Data Transfer Mechanism

Secure IoT data transfer in this research comes from the melding of two different protocols: MQTT

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(Message Queuing Telemetry Transport) for its small messaging footprint as it uses a publish-subscribe model which is ideal for applications with low-bandwidth applications and HTTP (Hypertext Transfer Protocol), which is used for devices to register and firmware updates (it uses a request-response model). As for data security, it's encrypted using the AES-256 standard.

$$MQTT_{transmission} = PubSub(data\ topic) \quad (5)$$

Eq. (5) illustrates MQTT protocols publish-subscribe model of data transmission.

$$HTTP_{communication} = RequestResponse(device\ server) \quad (6)$$

Eq. (6) indicates the HTTP protocol's request-response communication method.

$$EncryptedData = AES_{256}(OriginalData\ Key) \quad (7)$$

Eq. (7) illustrates AES-256 encryption using OriginalData as its 256-bit Key.

3.3 Data Visualization and Cloud Integration

The sensor data collected by the central unit instantly transmits it to an IoT dashboard hosted in the cloud for analysis and visualization which is accessible across all the kind of browsers. This platform serves both healthcare providers and patients by quickly providing access to health data quickly and alerting stakeholders of any sudden changes that require intervention.

3.4 Deep Learning Implementation

The proposed research brings two algorithms altogether, anomaly detection and risk prediction. Advanced Convolutional Neural Network for Health Anomaly Detection (ACN-HAD) identifies complex anomalies on health data for proactive health monitoring, while Health Risk Prediction using Health Risk Stratification Neural Network (HRS-NN) uses multilayer perceptron models to analyse health parameters to predict potential health risks.

In this research the deep learning models have been trained using an extensive simulated dataset. This dataset is featuring 10,000 data points from each of 100 subjects. It covered vital health parameters such as oxygen saturation in blood, blood pressure (systolic and diastolic), heart rate and hemoencephalography levels with the timestamps. This made it ideal for the deep learning models to learn to identify anomalies and categorize health risks as early as possible. The simulated data fed to the models also included several outlier points which represented adverse readings. The abnormal readings placed to ensure the usage of deep learning models that would result in a far more reliable system during both real-time health monitoring and early diagnosis of disease conditions.

3.5 Advanced Convolutional Neural Network for Health Anomaly Detection (ACN-HAD)

This research consists of an advanced deep learning model, Advanced Convolutional Neural Network for Health Anomaly Detection (ACN-HAD). ACN-HAD uses an advanced deep learning algorithm to make predictions from multivariate health data collected via sensors which detects health anomalies.

$$C_{l+1} = ReLU(W_l * C_l + b_l) P_{l+1} = MaxPooling(C_{l+1}) F_{l+1} = ReLU(W_f \cdot F_l + b_f) \quad (8)$$

The convolutional layer applies filters W_l to the input C_l, adding bias b_l, and applying the ReLU activation function. The pooling layer reduces the spatial dimensions, and the fully connected layer further processes the features.

3.5.1 Data pre-processing and feature engineering

The proposed model uses an expansive data set, gathering measurements of various health parameters such as Blood Pressure (Systolic and Diastolic), Heart rate, SpO2 levels, as well as Hemoencephalography (HEG) readings. Since the Timestamp column contains string values instead of datetime values for analysis purposes it has been converted to datetime format to track trends over time.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

$$F_{eng} = EngineerFeatures(X_{norm}) \quad (9a)$$

3.5.2 Outlier detection and handling

Outlier detection and handling are integral aspects of the proposed deep learning model which may produce an inaccurate anomaly detection result. Statistical techniques have been utilized such as Interquartile Range (IQR) method to effectively identify and handle the outliers. For each feature the model calculates its respective IQR value representing distance from 25th percentile up to 75th percentile to detect outliers which lie outside either first quartile or third quartile by some factor of its respective IQR value. The removal of these outliers based upon prevalence within the dataset.

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$$IQR = Q_3 - Q_1 O_{handled} = HandleOutliers(X\ IQR) \quad (10)$$

The IQR is computed as the difference between the 75th percentile Q_3 and the 25th percentile Q_1. Outliers in the data X are handled based on the IQR.

3.5.3 Data splitting for model validation

To ensure the model generalizes well to unfamiliar and novel data sets, the data has been divided into training and test sets. Here, the model is trained on one subset before its hyperparameters are tuned on another subset before its performance is reviewed on data never seen before - providing consistent estimates across random subsets of the data as an indicator of its potential real-world applications.

3.5.4 Utilization of autoencoders for feature extraction

Autoencoders enable automated feature selection and extraction through low-dimensional encodings learned that effectively reconstruct input data. Such reconstructions identify salient features from their input data that enable processing data with numerous dimensions.

.3.5.5 Sequence modelling for temporal anomalies

Sequence modelling techniques are used to capture temporal dependencies within data. More specifically, Long Short-Term Memory (LSTM) networks are integrated into model architecture which makes them suitable for learning from data with long-term dependencies - which makes them especially appropriate when applied to time series data where anomalies depend upon sequence of events.

$$ft = \sigma(Wf \bullet [ht-1,xt] + bf) \quad (11)$$

$$it = \sigma(Wi \bullet [ht-1,xt] + bi) \quad (11a)$$

$$C\tilde{}t = \tanh(WC \bullet [ht-1,xt] + bC) \quad (11b)$$

$$Ct = ft * Ct-1 + it * C\tilde{}t \quad (11c)$$

$$ot = \sigma(Wo\ [ht-1,xt] + bo) \quad (11d)$$

$$ht = ot * \tanh(Ct) \quad (11e)$$

LSTM cells use gates to regulate the flow of information. Here, f_t and i_t are the forget and input gates, $\tilde{C}_t$ is the candidate cell state, and h_t is the output.

3.5.6 Layered convolutional architecture

The ACN-HAD model uses a multilayered architecture composed of multiple Conv1D layers with differing filter sizes. The system utilizes these multiple Conv1D layers in order to extract advanced features from input data using this deep layered architecture, using them together with multiple Conv1D layers with differing filter sizes to capture increasingly complex features from input data. While initial layers might detect simple patterns like sudden spikes in heart rate, deeper ones can detect anomalous increases such as gradual but abnormal spikes in blood pressure levels.

$$Cl+1 = LeakyReLU(Wl * Cl + bl) \quad (12)$$
$$Pl+1 = MaxPooling(Cl+1) \quad (12a)$$
$$Sl+1 = SpatialDropout(Pl+1,rate) \quad (12b)$$
$$Al+1 = AlphaDropout(Fl,rate) \quad (12c)$$

The convolutional layer applies filters with LeakyReLU activation. MaxPooling reduces dimensions, and SpatialDropout and AlphaDropout are applied for regularization.

3.5.7 Activation functions and pooling layers

Leakage ReLU activation functions have been utilized to enable the proposed model to make sense of complex data sets. The MaxPooling1D pooling layers have also been implemented to lower feature map dimensionality and generalize more easily. Even when units become inactive due to gradient leakage, some information still leaks through the MaxPooling layers which serve as down sampling filters. This reduces the computational costs while decreasing overfitting and making detection independent from the orientation changes.

$$Al+1 = LeakyReLU(Cl+1) \quad (13)$$
$$Pl+1 = MaxPooling(Al+1) \quad (13a)$$

The LeakyReLU function introduces non-linearity, allowing the proposed model to learn more complex patterns.

$$Sl+1 = SpatialDropout(Cl+1\ rate) \quad (14)$$
$$Al+1 = AlphaDropout(Dl,rate) \quad (14a)$$

Advanced regularization techniques obtained by implementing spatial dropout and alpha dropout regularization algorithms have proven highly successful when applied to Conv1D layers with dense structures, particularly when combined with activation function ELU (Exponential Linear Unit). Spatial Dropout regularizes Conv1D layers by dropping entire feature maps. Alpha Dropout, on the other hand, is specifically tailored to dense layers - especially effective with ELU activations.

3.5.8 Training process and hyperparameter optimization

Optimization of deep learning models utilizes both manual tuning and automated hyperparameter

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optimization techniques like Bayesian Optimization to achieve an equitable result. To find the best combination of hyperparameters and efficiently managing model complexity the trade-off can be used and calculated as

$$\Theta^* = \text{argmin}_\Theta \text{BayesianOptimization}(L(D;\Theta)) \quad (15)$$

Bayesian Optimization have been implemented for a set of hyperparameters Θ^* which minimizes the loss function L over the dataset D.

$$L\text{custom} = Xwi \cdot Li(D;\Theta) \quad (16)$$

With custom loss functions in the Eq. (16), different types of anomalies are weighted using the weights for each type of anomaly. Each individual loss function is represented in equation L_i and then multiplied by its weight w_i, which is then summed and returned by custom loss.

3.5.9 Advanced training strategies

Creating and training a model involves more than feeding the batches of data. Several techniques have been deployed such as Gradient Accumulation which allows for training with larger datasets without impacting computational efficiency. The Learning Rate Annealing implemented for the models which can gradually lower learning rates during training to improve convergence over time.

$$\Theta\text{new} = \Theta - \eta \cdot \nabla L(D;\Theta) \quad (17)$$

$$\eta\text{new} = \text{LearningRateAnnealing}(\eta) \quad (18)$$

Gradient Accumulation updates the model parameters Θ using the gradient of the loss function ∇L. Learning Rate Annealing gradually reduces the learning rate η for better convergence.

3.5.10 Cross-Validation techniques

Robust model evaluation can be achieved using advanced cross-validation techniques such as timeseries cross-validation which assess the temporal nature of data points, to test on unseen points that simulate real-world scenarios and ensure robust anomaly detection models are created. A variety of visual and statistical approaches are used to assess anomaly detection models' performance.

$$\text{CV}_{\text{score}} = \frac{1}{k}\sum_{i=1}^{k} \mathcal{F}\left(\text{Model}\left(\text{D}_{\text{train}_i};\Theta\right), \text{D}_{\text{test}_i}\right) \quad (19)$$

Time-series cross-validation evaluates the model across different folds. The model trained on $\text{train}_\text{D}^{(i)}$ is tested on $\text{test}_\text{D}^{(i)}, and\ F$ is the evaluation function.

3.5.11 Interpretability

Analysis requires using both visual and statistical methods to assess an anomaly detection model's performance, which utilizes traditional metrics as well as innovative visualizations for an in-depth evaluation. By plotting anomaly scores across a test dataset, prediction confidence of the model can be easily gauged while distinguishing levels of anomalous behavior. Time series analysis has been employed to demonstrate the model's temporal anomaly detection capabilities, showing its proficiency and limitations when it comes to recognizing temporal irregularities - an essential task in real-time monitoring. Three distinct metrics were designed that are automatically calculated and visualized to provide both quantitative and qualitative evaluations, creating a holistic evaluation of its practical performance.

The Accuracy measures the overall correctness of the model and is defined as the ratio of correctly predicted instances (both positive and negative) to the total number of instances.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \quad (20)$$

Where True Positives (TP) are correctly identified positives and True Negatives (TN) are correctly identified negatives.

Precision assesses the model's ability to correctly identify only relevant instances. It is particularly important in scenarios where the cost of false positives is high.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (21)$$

Recall measures the model's ability to correctly identify all actual positives. It is crucial in situations where missing a positive instance (false negative) is undesirable.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (22)$$

The objective of the algorithm module is to provide a structured outline describing the Advanced CNN for Health Anomaly Detection in the algorithm 1, from data preprocessing to model evaluation, including critical steps such as data normalization, model architecture definition, training with early stopping, performance visualization, etc. A comprehensive deep learning pipeline to detect health anomalies in the dataset.

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3.6 Health Risk Prediction Using Health Risk Stratification Neural Network

The Health Risk Stratification Neural Network (HRS-NN) model is a multi-layer perceptron (MLP) which is a type of feedforward artificial neural network. Consisting of multiple dense layers with a 'ReLU' activation function which introduces non-linearity thus allowing the model to learn complex patterns in the data.

$$H_{l+1} = \mathrm{ReLU}(W_l \cdot H_l + b_l) \quad (23)$$

Eq. (23) represents the ReLU activation function applied in a dense layer of the MLP. It introduces non-linearity, allowing the model to learn complex patterns.

$$\frac{\partial H_{l+1}}{\partial H_l} = \mathrm{ReLU}'(W_l \cdot H_l + b_l) \cdot W_l \quad (24)$$

Eq. (24) represents the derivative of the ReLU activation function, which is crucial for backpropagation during training. It calculates the gradient of the activation function with respect to the input.

3.6.1 Data Preprocessing for health risk prediction

While the feature set is consisting of various health parameters have been carefully engineered. The new features are created to capture the complexity of the health data better. For instance, polynomial features have created to model non-linear relationships between health parameters and risk levels.

$$F_{eng} = \mathrm{PolynomialFeatures}(X) \quad (25)$$

Eq. (25) is the summation of polynomially engineered features across the dataset which is showing the collective impact of these features.

$$\int F_{eng}\, dX = \int \mathrm{PolynomialFeatures}(X)\, dX \quad (26)$$

Eq. (26) represents the summation of polynomially engineered features over the dataset which indicates the accumulation of the features' effects.

3.6.2 Target variable encoding

The target variable has been transformed using the label encoding. It also converts the categorical labels into a numerical form. The next process is to transform the numerical labels into a binary matrix by the One-Hot Encoding method which is essential for multi-class classification.

$$Y_{label} = \mathrm{LabelEncode}(Y) \quad (27)$$

Eq. (27) performs the conversion of categorical labels to a form which could be provided to further processing for preparing the target variable.

$$Y_{one\text{-}hot} = \mathrm{OneHotEncode}(Y_{label}) \quad (28)$$

Eq. (28) converts the encoded target variable into a binary matrix form which is necessary for the multi-class classification in neural networks

Algorithm 1: Advanced CNN for Health Anomaly Detection

1: Load and preprocess the health data from CSV.
2: Normalize the data excluding non-feature columns.
3: Split the dataset into training and testing sets.
4: Define the CNN model with layers: Conv1D, MaxPooling1D, Dropout, Flat-ten, and Dense.
5: Compile the model with the Adam optimizer and binary crossentropy loss.
6: Train the model using early stopping based on validation loss.
7: Evaluate the model's performance and generate a classification report.
8: Visualize the training and validation metrics over epochs.

3.6.3 Feature normalization

The input features of the dataset undergo normalization using MinMaxScaler and scaling the feature values to a range of 0 to 1. The purpose of the normalization is to ensure that various measurements of health are on the same scale and therefore equally contribute to the ability of the model to make predictions.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (29)$$

Eq. (29) normalizes the input features of the data to a range of 0 to 1 which ensures a uniform contribution of each feature to the model.

$$\frac{dX_{norm}}{dX} = \frac{1}{X_{max} - X_{min}} \quad (30)$$

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Eq. (30) represents derivative of the normalization feature indicates the sensitive normalized value's changes in the original feature.

3.6.4 Encoding and normalization

The target variable undergoes label encoding followed by one-hot encoding to convert it into a format suitable for multi-class classification j. The input features are normalized using MinMaxScaler, ensuring that all variables contribute equally to the model's learning process.

$$\mathrm{Y_{encoded}} = \mathrm{OneHotEncode}\big(\mathrm{LabelEncode(Y)}\big) \quad (31)$$

$$\mathrm{X_{norm}} = \frac{\mathrm{X} - \min(\mathrm{X})}{\max(\mathrm{X}) - \min(\mathrm{X})} \quad (32)$$

Eq. (32) is vital as it normalizes the input features so that they all contribute approximately proportionately to the learning, hence maintaining a balance across various scales of data.

3.6.5 Model architecture: HRS-NN

The model is a Sequential model comprising two Dense layers, each with 50 neurons. These layers use 'ReLU' (Rectified Linear Unit) activation functions to introduce non-linearity, allowing the model to capture complex relationships in the dataset.

$$\mathrm{H_{l+1}} = \mathrm{ReLU}(\mathrm{W_l} \cdot \mathrm{H_l} + \mathrm{b_l}) \quad (33)$$

Eq. (33) represents the HRS-NN model architecture where each layer applies the ReLU activation function to introduce non-linearity to enable the model to learn complex data patterns.

3.6.6 Model compilation

The model is compiled using the 'Adam' optimizer. This is a very efficient optimizer that works well with large datasets and with a deep network architecture. The loss function is 'categorical cross-entropy'. This is the metric used by neural networks that are trained to classify objects into multiple categories.

Compile(HRS-NN,'adam','categorical_crossentropy') (34)

Eq. (34) shows how HRS-NN model is compiled where 'adam' optimizer is used and 'categorical cross-entropy' is the loss function that is being used. Which is called for multi-class classification tasks.

3.6.7 Training and optimization

Advanced techniques like grid search and random search have been implemented for hyperparameter optimization. These methods work by systematically testing different combinations of hyperparameters (e.g., number of neurons, layers, learning rate) to see which work most effectively.

$$\Theta^* = \mathrm{argmin}_{\Theta}\,\mathrm{HyperparameterOptimization}(\mathcal{L}, \mathrm{D}) \quad (35)$$

Eq. (35) represents the process of finding the optimal set of hyperparameters of the model by minimizing the loss function *L* over the dataset *D*.

3.6.8 Customized loss function and evaluation metrics

To get the best performance possible the custom loss functions that can incorporate the unique structure of health risk prediction have been explored, in addition to using categorical cross-entropy as the loss. The evaluation metrics were expanded to include weighted precision, recall, and F1-score, as these will provide a more comprehensive idea of how well the model is performing across the various health risk categories.

$$\mathcal{L}_{\mathrm{cso}} = \sum \mathrm{w_i} \cdot \mathcal{L}_i(\mathrm{D}; \Theta) \quad (36)$$

Eq. (36) describes a custom loss function which is customized to the specific nature of health risk prediction, where w_i are weights assigned to different types of health risks.

3.6.9 Model training

The HRS-NN model was trained for 75 epochs in total with a batch size of 32. Performance on unseen data during training is also crucial for avoiding overfitting and was made possible by using a validation split of 20% of the training data.

$$\mathrm{Train}(\mathrm{HRS\text{-}NN}, \mathrm{D_{train}}, \mathrm{epochs} = 75, \mathrm{batch\_size} = 32) \quad (37)$$

Eq. (37) details the training process of the HRS-NN model, which is specifying the number of epochs, batch size, and emphasizing the importance of validation data to avoid the overfitting.

3.6.10 Cross-Validation and robust evaluation

The model is rigorously evaluated using techniques such as stratified k-fold cross validation that ensure the model is evaluated

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consistently across different subsets of the dataset to ensure the evaluations are less biased.

$$\mathrm{CV_{score}} = \frac{1}{k}\sum_{i=1}^{k} \mathrm{ModelEvaluate}\left(D_{train}^{(i)}, D_{test}^{(i)}\right) \tag{38}$$

Eq. (38) represents the stratified k-fold cross-validation process. The dataset is then divided into *k* folds, and the model is trained and evaluated *k* times. It performs N folds of cross validation by train the data and testing by each fold as the test set. The remaining folds are used in order as the training set.

$$\mathrm{Var_{CV}} = \frac{1}{k-1}\sum_{i=1}^{k}\left(\mathrm{CV}_{score}^{(i)} - \overline{\mathrm{CV}_{score}}\right)^2 \tag{39}$$

Eq. (39) calculates the variance in cross-validation scores across folds. If the variance is high, then it's possible that the model doesn't generalize well to new data.

3.6.11 Confusion matrix and performance metrics

A confusion matrix has been generated with percentage values to understand the model's predictive accuracy for each class against every other class. The confusion matrix shows the model is particularly good at identifying the normalcy class versus the abnormal class.

$$C_{ij} = \sum_{n=1}^{N} \mathbb{1}\left(y_{true}^{(n)} = i \wedge y_{pred}^{(n)} = j\right) \tag{40}$$

Eq. (40) defines the confusion matrix element C_{ij}, which counts the number of instances where the true class is *i* and the predicted class is *j*.

$$\mathrm{Accuracy}_i = \frac{C_{ii}}{\sum_{j=1}^{M} C_{ij}} \tag{41}$$

Eq. (41) calculates the accuracy for each class *i* based on the confusion matrix. It is the ratio of correctly predicted instances of class *i* to the total instances of class *i*.

3.6.12 Training and validation performance visualization

Training and Validation Accuracy calculates the proportion of correct predictions (both true positives and true negatives) out of all predictions made by the model on the training and validation sets.

$$\mathrm{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \tag{42}$$

Test Accuracy measures how well the model performs on unseen data (the test set). It is the ratio of correct predictions to total predictions made on the test set.

$$\text{Test Accuracy} = \frac{\text{Correct Predictions on Test Set}}{\text{Total Predictions on Test Set}} \tag{43}$$

Training and Validation Loss Represents the loss function used during the training and validation of the model. Here, y_i is the true label, and $\hat{y}_i$ is the predicted label. The loss function quantifies how well the model's predictions match the actual labels.

$$\mathrm{Loss} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \tag{44}$$

To monitor the model's ability to learn from the data, the training and validation accuracy over epochs have plotted. This allowed us to observe the model's improvement over time and to verify that the model was not overfitting, as indicated by the convergence of training and validation accuracy.

$$\mathrm{Accuracy_{epoch}} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \tag{45}$$

Eq. (45) measures the accuracy of the model at each epoch during training and validation. It helps in observing the learning curve of the model.

$$\mathrm{Loss_{epoch}} = \mathcal{L}\left(D_{train}; \Theta_{epoch}\right) \tag{46}$$

Eq. (46) represents the computation of loss function for each epoch. Monitoring this helps in understanding the model's convergence behavior.

The procedure for a deep learning process using a Multilayer Perceptron (MLP) shown in the algorithm 2. The process consists of loading and preprocessing health risk data from a CSV file, specifying the MLP's architecture with two hidden layers, as well as compiling the model with specific hyperparameters, training the model, and evaluating its accuracy across training data.

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Algorithm 2: Health Risk Stratification Neural Network

CSV file 'healthdata.csv' with health risk data
Target column 'Health Risk'
Model architecture parameters: 2 hidden layers each with 50 neurons, 'relu'activation
Output layer parameters: 'softmax' activation, number of classes derivedfrom target
Training parameters: 75 epochs, 32 batch size, 20% validation split
Random state for split: 42
Optimizer: 'adam'
Loss function: ' categorical crossentropy'
Metrics: ' Train, Test and Overall Accuracy'
procedure TRAIN_HEALTH_RISK_CLASSIFIER_MLP
  Load Data: Import CSV data into DataFrame.
  Preprocess Data: Drop non-feature columns from DataFrame.
    Encode target ' Health Risk' and normalize features.
  Split Data: Partition data into training and test sets.
  Build Model: Initialize Sequential model and add layers.
  Compile Model: Set optimizer, loss function, and metrics.
  Train Model: Fit model on training data.
end procedure

4. RESULTS AND DISCUSSION

These results show that using algorithms for health risk prediction and anomaly detection in person-specific long-term patterns turn out to yield significant results, the ACN-HAD model showed potential to detect anomalies in the data as it reaches high accuracy, precision, and recall, which shows it is capable of distinguishing among the normal and abnormal health state of a person.

The health risk prediction tailored model HRS-NN achieved a remarkable accuracy further highlighting that specialized models are the best fit for any given task. The choice of two separate algorithms not only allowed for optimized performance on diagnostics but also for each algorithm to be best suited for the complex and nuanced characteristic of its respective task, early health risk detection or vital-sign-based health anomaly detection. Overall, this dual-algorithm approach enhanced the performance of the entire system and highlights the importance of task-specific model selection across the domain of healthcare analytics.

4.1 Anomaly Detection

In addition to diagnostics the exceptional performance of the ACN-HAD model for real-time health anomaly detection in IoT-based healthcare has been demonstrated. With an improved accuracy of approximately 98.8% and precision and recall rates of approximately 99% for both anomaly classes this model achieves high reliability and balanced class performance to differentiate between normal and anomalous states for critical health parameters. This level of accuracy and precision in real-time patient monitoring and early health risk detection marks a significant leap forward in-patient healthcare.

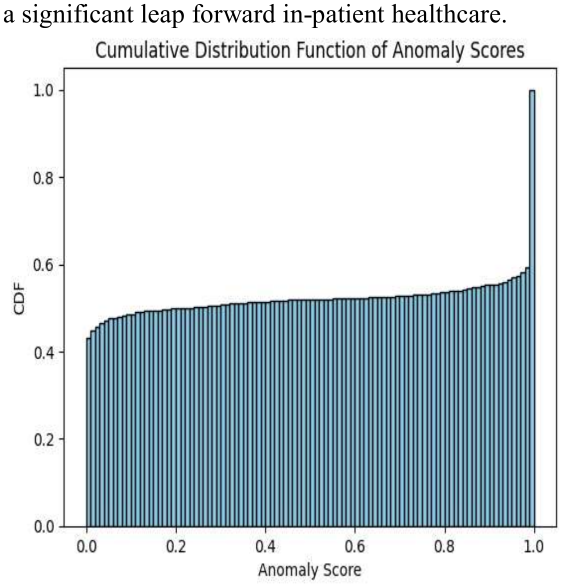

Figure 2: CDF of Anomaly Scores Indicating Detection Thresholds

The Cumulative Distribution Function (CDF) plot in the figure 2 gives a holistic view of the

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anomaly scores assigned to the test data. The plot is the CDF of absolute error (anomaly scores) values. A generally increasing curve indicates that the model recognizes a majority of the data by marking it with low outlier scores. The steep rise at the end of the curve indicates a small number of data points with high outlier scores. This sharp rise would be the point at which the model begins to recognize true anomalies at an increasing rate. The placement of this outlying score threshold is critical; it is directly reflective of the concept of normal behavior of the dataset and it becomes the balance between the sensitivity to true anomalies and the positives.

The Time Series Anomaly Highlighting plot in the figure 3 the plot of continuous stream of time-series data in blue and position the instances identified as anomalies by the model as a red line above the data. This separation of the data stream allows one to observe the efficacy of the model in real time anomaly detection and to understand the temporal patterns of anomalous behavior present in the data. In this case the model is very sparse in its predictions, only flagging those data points which very strongly do not fit the established pattern. Understanding the construction and operation of the model in this way is essential for understanding the dynamical properties of its detection capability and for controlling false positive rates in continuous monitoring applications.

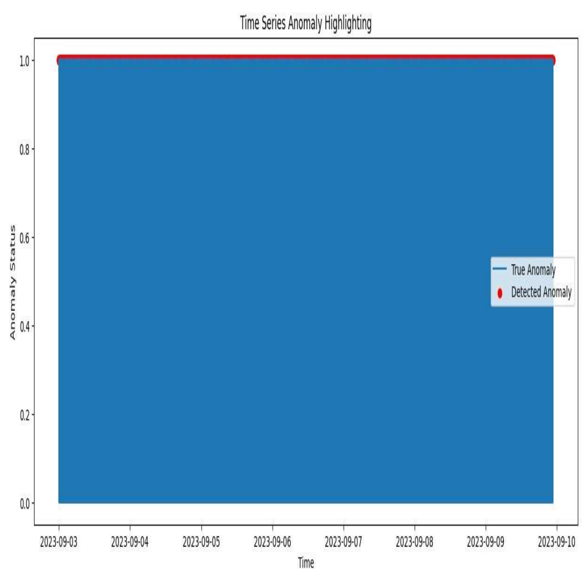

Figure 3: Temporal Visualization of Anomaly Detection Performance

The Anomaly Scores Plot in the figure 4 is a scatter plot of the anomaly scores for the test data. It visualizes individual data points as a function of their respective anomaly score. The data points clustered near the bottom with lower scores represent normal behavior. The data points with higher scores are the potential anomalies. The clear segregation of lower and higher scores demonstrates the model's ability to discern between normal and anomalous states quite effectively. The distribution of these scores can be particularly critical for setting up a threshold-based system for anomaly alerts.

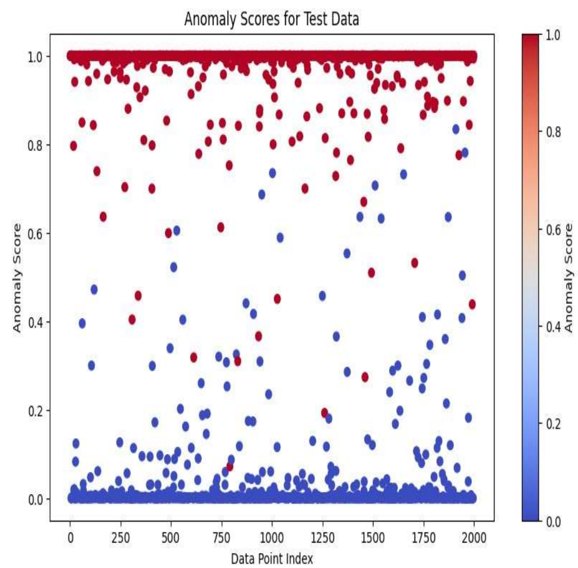

Figure 4: Distribution of Anomaly Scores

This ROC plot in the figure 5 clearly displays that classification was perfect with an area under the curve (AUC) value of 1, which signifies no errors were committed when differentiating between classes using this model. Furthermore, its steep rise at threshold close to zero signifies its superior sensitivity/specificity capabilities as well as an exceptional discriminative power for detecting anomalies.

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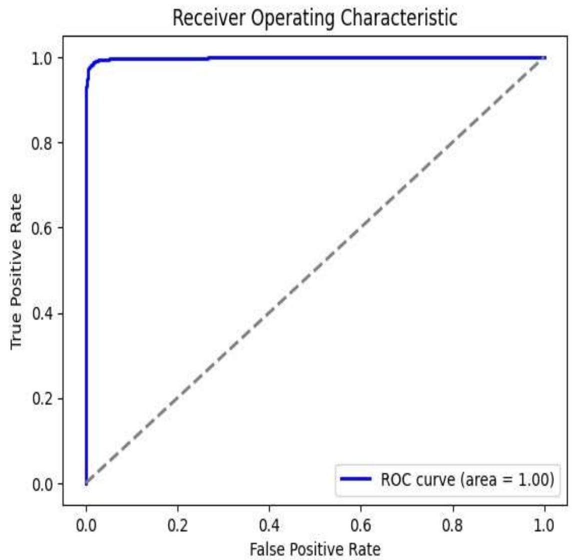

Figure 5: ROC Curve Depicting Model's Discriminatory Capacity

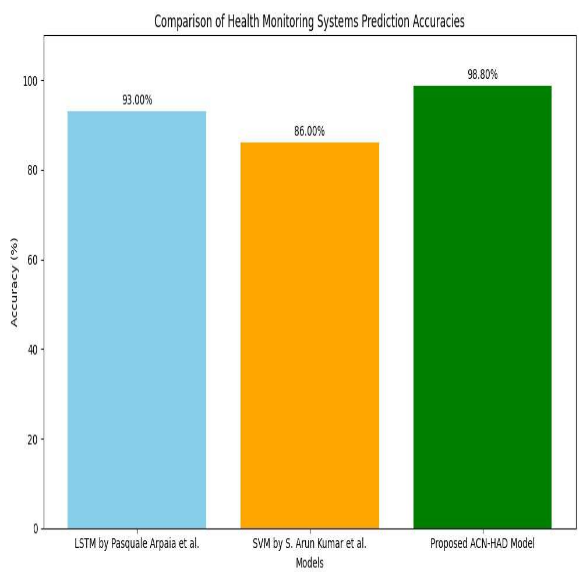

Figure 6: Comparison of Accuracies of Different Models

Compared with the existing studies, the proposed model in the figure 6 shows a notable improvement. In the work of Pasquale Arpaia et al. [49], which focuses wearable technology on vital monitoring, the Long-Short-Term-Memory Autoencoder algorithm was used and achieved just above 93% accuracy. The high accuracy by the proposed model is more effective in identifying subtle and complex anomalies in health data. This is an essential task for proactive patient monitoring.

When compared with the work conducted by S. Arun Kumar et al. [50], the proposed model outperforms Kumar et al. on two key aspects in which, a smart health monitoring system based on the Support Vector Machine (SVM) model have proposed for disease detection. Several sensors were used to record the patient's health, and the system communicated with the doctors through the ThingSpeak cloud. A trained machine learning model was used to detect diseases, and it achieved an accuracy of 86% in real-time scenarios.

In comparison, the proposed ACN-HAD model achieves superior accuracy and precision of 98.8% and 99%, respectively, in health anomaly detection. This outperforms the other systems. The strength of this ACN-HAD model lies in the ability to provide high accuracy on the multifarious time-series comparison and the use of the LSTM networks provides a comprehensive understanding of the evolution of health data, which is important for accurate predictions of health risks. Another important property of the ACN-HAD is its high recall rate which is very important in healthcare applications as missing a health anomaly may redound to unintended consequences.

Comparisons with state-of-the-art studies in the literature show that the ACNHAD model builds on solid foundations set by research that precedes it while performing with greater accuracy, precision, and recall, to stand as a significant contribution to the application of smart healthcare in the field, improving patient care and health outcomes.

4.2 Prediction

The proposed model for prediction capitalizes on a dataset that embeds vital health parameters, namely, systolic and diastolic blood pressure (BPsys, BPdia), heart rate, oxygen saturation levels (SpO2), and hemoencephalography (HEG) data. These measurements form the background on which the Health Risk Stratification Neural Network (HRS-NN) is laid; allowing us to twine a sophisticated tapestry for health risk assessment. These parameters have analyzed to stratify health risk as Low, Medium, and High, offering a clear, categorical view of the immediately impending

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health risks based on collected measurements. By analyzing the correlations between the collected vital signs, the HRS-NN has indeed demonstrated a successful approach to predicting health risks. As intended, its predictive model can identify those with an increased cardiovascular, respiratory, or neurological disease risk, including cardiovascular diseases. By combining data such as heart rate measurements as well as blood pressure (BPsys, BPdia), the HRS-NN predicts diseases related to cardiovascular before the patient is even aware. In addition to providing an early warning, this is yet another clear demonstration of its success at providing preventative healthcare. By analyzing SpO2 levels, this model allows for accurate predictions of respiratory disorders like asthma and COPD - emphasizing the value of oxygen saturation monitoring in terms of respiratory health assessment.

The evolution of the model's accuracy during the training process is summarized in this figure 7. The figure shows how both training and validation accuracies surge during the first 20 epochs, denoting a phase of rapid learning where the HRS-NN is adept at capturing the underlying patterns of the dataset. Once both lines converge and continue running in parallel beyond epoch 20, this indicates that the model's learning has stabilized. It's also worth noticing that the validation accuracy does not drop significantly below the training accuracy, as is common in the case of overfitting. Instead, the model eschews overfitting, showing generalizable performance throughout training.

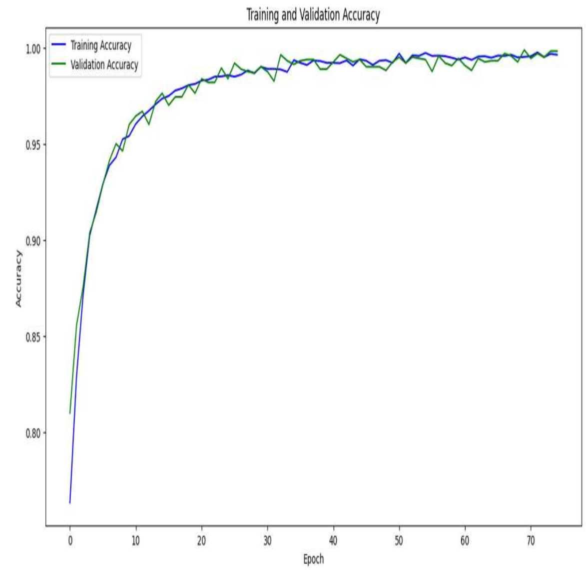

Figure 7: Training and Validation Accuracy over Epochs

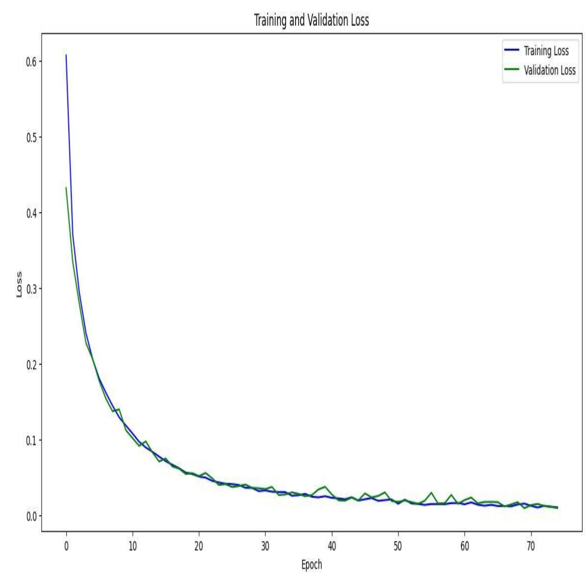

Figure 8: Training and Validation Loss over Epochs

Unlike the accuracy plot, in the figure 8 the loss over time is the figure plotted. The loss function is a measure of how far off the model's predictions are from the actual values. Initially, the loss drops rapidly so the model is quickly learning the weights and biases that minimize its predictions. As the epochs progress, the training and validation losses level off which indicates that the model isn't learning to further reduce the error significantly below a certain threshold, meaning that the model has reached the optimal weights. This "plateauing" is a good sign that the model is

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converging. Furthermore, the proximity of the training and validation loss lines at the very end of training demonstrates that the model had a great ability to generalize. Finally, the curves being smooth signifies that the model is not exhibiting high variance or erratic learning behavior which can happen when models are too complex.

The accuracy of the predictions is not only high but also balanced across different classes, as shown in the bar chart comparing actual and predicted counts for each class in the figure 9. This balance is crucial for ensuring the model is not biased towards any class, which is often a challenge in multi-class health risk predictions. The model's precision in classification is further validated by the confusion matrix shown in the figure 10 which shows a high percentage of true positive rates with minimal false positives and false negatives.

The confusion matrix is a fundamental evaluation tool for classification models as shown in the figure 10 which presents the model's performance in detail for each class, showing the percentage of predictions that are true positive, false positive, false negative, and true negative, respectively. High percentages in the diagonal from the upper left to the lower right reflect a high true positive rate. Low percentages off the diagonal demonstrate the few false positives and false negatives that are needed to minimize misdiagnoses in a health risk stratification context. The uniformity of diagonal percentages across classes also shows that the model is not only accurate, but is consistent in its predictions across different types of risk, which is essential for its usage in a clinical setting, where consistency is key for patient trust and clinical decision-making.

The plot is a comparative visualization of the actual versus predicted classification distribution for three classes class 0, class 1, and class 2 in Figure 11. Indicated by the density of data at different values. The width represents the probability density of the data at different values, with wider sections containing more densely packed data points. The actual data distribution appears to have a greater spread across the classes, indicating a more varied actual class distribution. The predicted data has a greater concentration around the median, suggesting the model's predictions are more confident, or less varied. The 'necks' being thin suggests there is a lower density or fewer data points at the extremes, which is common in classification tasks where the central classes are often more populated. The internal box plots show the median and interquartile ranges, providing a quick visual reference to the central.

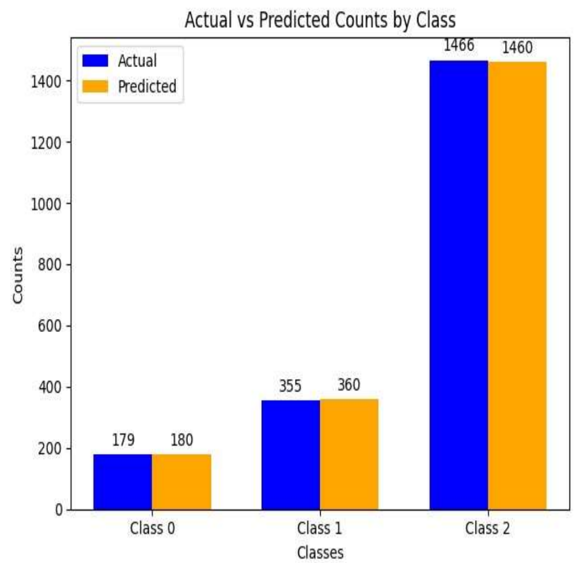

Figure 9: Comparison of Actual Versus Predicted Counts by Class

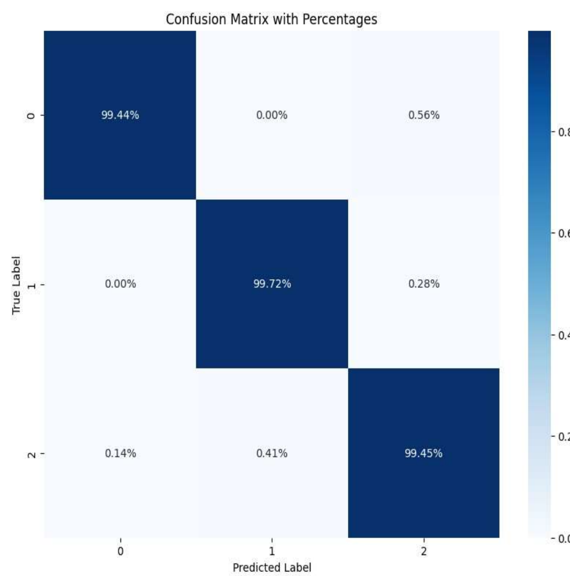

Figure 10: Confusion Matrix with Percentage Values

The Health Risk Stratification Neural Network (HRS-NN) model has illustrated exemplary performance within the landscape of health risk prediction. Finally, a training accuracy

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of 99.64%, validation accuracy of 99.5%, and overall test accuracy of 99.3% indicate that the model can accurately predict health risks based upon a comprehensive analysis of several health parameters.

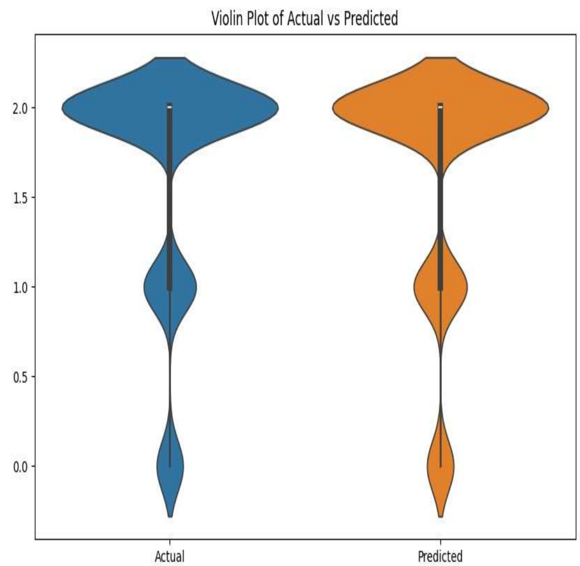

Figure 11: Plot of Actual vs. Predicted Class Distributions

The distinctiveness of the model is further evidenced in comparison with existing studies, mentioned in Figure 14. For instance, Mohana et al. [51] explored IoT in healthcare using CNN. Their study demonstrated a training accuracy of 99.6% and a testing accuracy of 86.3%. It is remarkable to note that there existed substantial disparity in their accuracies, suggesting overfitting. This issue is seemingly curtailed in the proposed model which stands out in terms of consistently high accuracy, in all phases, pointing towards a balanced and more generalizable approach to predicting health risks.

The proposed model also significantly outperforms the LovHealth system [52] by Rafly Arief Kanza et al., which uses Random Forest and achieved an accuracy of 82.6%. In comparison, the proposed model demonstrates significantly higher accuracy thus showing its ability to handle complex health data. Additionally, the work of Md. Reazul Islam et al. on an IoT-based remote monitoring system [53] which uses a CNN model and achieves 98.2% overall accuracy, is surpassed by the proposed model's greater accuracy and high precision which are crucial for health risk prediction.

The superior performance of the HRS-NN model, especially against overfitting and high accuracy is maintained over three phases of evaluation illustrating its reliability and effectiveness concerning healthcare application. As a high precision, early prediction of health risk is what can be vital in a healthcare setup the model's performance in precision is highly promising and can play a big part in timely and effective medical interventions.

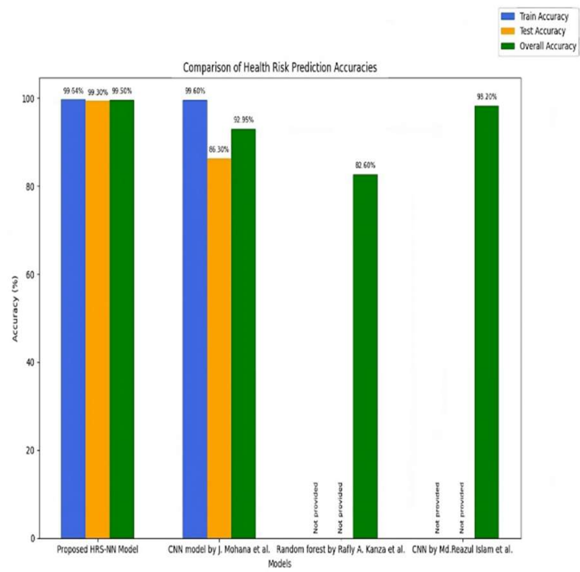

Figure 14: Comparison of Different Models' Accuracy

The comparative study of these models establishes its advancement over existing methodologies especially in terms of complex health data-based predictions and positioning this work as a significant contribution in health risk prediction using advanced deep learning techniques.

5. CONCLUSION

This research paper has concentrated on fulfilling the objective with capability of combining several diverse technologies, which is a key step towards addressing various complex environmental issues facing the world. The application of IoT enabled cutting edge Deep Learning algorithms will assist the healthcare industries to meet the challenges ahead. The research exhibits an innovative solution for Remote Patient Monitoring (RPM), which

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outperforms the existing techniques by introducing, data collection and analytics, which demonstrate remarkably accurate results, by identification of health anomalies and stratification of risks, validating the approach and proving its value. Successful care transformation lies in providing healthcare professionals with disruptive, state-of-the-art tools. The success of the system is its unique ability to give healthcare providers tools that are designed specifically for the patient. Accurate, timely insights into patient health allow for proactive intervention and immediate, customized treatment strategies. The system's wider application as in real-time particulate matter monitoring integrated with health parameters further operates to excite. Environmental influences on individual health outcomes have long been recognized as intertwined; the study of this complex relationship serves to further advance knowledge. The future implications of the research couldn't be more dramatic: by giving hope to patients. As healthcare becomes more personalized, data-driven, and responsive to patient needs, the imperative becomes inescapable. Revolutionizing healthcare delivery depends on arming healthcare providers with breakthrough technologies tailored for patient needs. These capabilities transform the technology from traditional healthcare systems which are inherently limited in their capabilities to this integrated technology that can expand exponentially. The introduction of this integrated technology may well begin to define an entirely new paradigm for medical treatment and its results are crystal clear. The research study uncovers the dramatic realities of reduced healthcare costs and system burdens.

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