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IoT-Based Health Monitoring System: Design, Implementation, and Performance Evaluation

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Nouby M. Ghazaly
Professor, Faculty of Engineering,
South Valley University, Qena 83523, Egypt.
https://orcid.org/0000-0001-6320-1916

Dr. Naveen Jain
Associate Professor, Mechanical Engineering,
Shri Shankaracharya Institute of Professional Management and Technology, Raipur, India
naveenjain@ssipmt.com

Abstract

The Internet of Things (IoT) technology's rapid improvements have opened the door for creative solutions across a range of industries, including healthcare. An IoT-based health monitoring system that aims to revolutionize patient care and healthcare administration is described in this study along with its design, implementation, and performance evaluation. To continuously gather and send health-related data, our system makes use of a network of wearable sensors and gadgets that are seamlessly incorporated into a patient's daily life. Vital indicators like heart rate, blood pressure, temperature, and activity levels are tracked by these devices. To enable real-time analysis and storage, the data is safely sent to a centralized server. Both patients and healthcare professionals can access this information through a user-friendly smartphone application, enabling proactive healthcare decision-making. An effective and scalable architecture is used in the implementation of this system to guarantee the confidentiality, accuracy, and reliability of the data. The data is analyzed using machine learning algorithms, which enables the early identification of abnormalities and trends that could portend serious health problems. The system can also produce warnings and notifications, ensuring prompt intervention when it's necessary. Our IoT-based health monitoring system's performance review indicates how well it performs in terms of enhancing healthcare outcomes. The solution gives healthcare professionals immediate access to crucial health information, allowing them to personalize treatment regimens, offer remote consultations, and make educated judgements. Continuous monitoring benefits patients by allowing for early intervention, fewer hospital stays, and an improvement in general health. Additionally, the system's scalability and versatility make it appropriate for a variety of healthcare settings, including small-scale home care and extensive hospital networks.

Keywords

Internet of Things, Health Monitoring System, Security, Decision making, Machine Learning

1. Introduction

A new era of patient-centred care has begun as a result of the fusion of healthcare and technology, and this development has the potential to completely change how we keep track of and manage our health. The Internet of Things (IoT), one of the most promising technological developments in this field, has spawned creative healthcare solutions like IoT-based health monitoring systems. In order to give an in-depth examination of its transformational impact on healthcare, this article looks into the design, implementation, and performance evaluation of such a system. An [1] ageing population, an increase in the prevalence of chronic diseases, and a rise in the demand for more readily available and reasonably priced healthcare services are all contributing to a substantial paradigm change in the healthcare industry.

Patients only seek medical attention when they suffer symptoms or need treatment, which is common in traditional healthcare practises. For managing chronic disorders, avoiding diseases, and enhancing general wellbeing, this strategy is less than optimal.

IoT-based health monitoring systems, [2] on the other hand, provide a proactive and ongoing approach to healthcare. These systems utilise real-time data collection, transmission, and analysis capabilities of connected devices, sensors, and data analytics. Key elements of this ecosystem include wearable technology, home monitoring tools, and mobile applications. These tools allow people to monitor their vital signs, measure their activity levels, and manage their health from the comfort of their own homes.

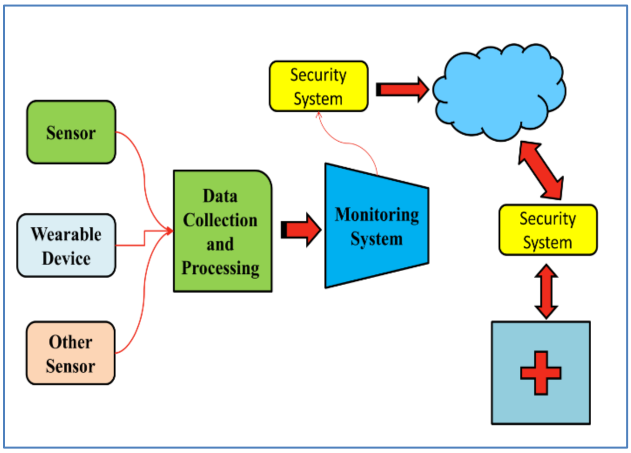

Figure 1: Overview of Proposed system

Such systems may change the emphasis from reactive therapy to preventative care and early intervention, enhancing healthcare outcomes and lowering costs. As it entails integrating numerous components into a smooth and safe framework, as shown in figure 1, designing an IoT-based health monitoring [3] system is a challenging task. For instance, wearable sensors must be convenient, inconspicuous, and able to gather precise data. These sensors frequently keep an eye on a variety of vital signs, such as heart rate, blood pressure, temperature, and breathing rate, giving doctors a complete picture of the health of a patient. Wireless communication [31] protocols are then used to transport the data to a central server, making it available for analysis and decision-making. Similar importance must be placed on the system's installation phase. To manage the enormous volumes of data produced by the sensors, a reliable and scalable infrastructure must be created. Furthermore, data security and privacy are crucial because health information is extremely sensitive and governed by strict laws. To protect patient information and guarantee compliance with privacy laws, encryption, authentication, and access control systems must be in place [4].

After being put into place, the system is subjected to a thorough performance evaluation to see how well it affects healthcare outcomes. To [5] evaluate the correctness, dependability, and responsiveness of the system, real-world data is gathered and examined. Machine learning algorithms are frequently used to find trends and abnormalities in data, allowing for early intervention and individualised medical advice. Additionally, user opinions and satisfaction are very important in determining how well the system is used and accepted by patients and healthcare professionals. IoT-based health monitoring systems have a huge potential impact. These technologies give patients the ease of ongoing monitoring and the power to take an active role in their healthcare. A [6] timely warning or message may encourage someone to make a healthier decision or seek medical help when necessary, potentially lowering hospital stays and ER visits. Healthcare professionals' capacity to make knowledgeable judgements, give remote consultations, and customise treatment regimens to patients' requirements is improved by access to real-time health data. Better patient outcomes and more effective healthcare delivery may result from this. Additionally, IoT-based health monitoring systems are appropriate for a variety of healthcare settings due to their scalability and versatility. They [32] can be used in big hospital networks, home healthcare, assisted living facilities, and remote patient monitoring. They have the potential to revolutionise healthcare delivery throughout the continuum of care thanks to their adaptability. With [7] the potential to enhance patient care, lower healthcare costs, and advance general wellbeing, IoT-based health monitoring systems are a cutting-edge approach to healthcare. Realising this promise will require careful consideration in the design, implementation, and performance evaluation of such systems. In order to contribute to the continuous transformation of healthcare in the digital age, this article intends to give a thorough exploration of the design principles, implementation issues, and performance outcomes connected with IoT-based health monitoring systems.

The contribution made by this paper to the subject of IoT-Based Health Monitoring Systems is given as:

- The article discusses solutions for real-world implementation issues, such as power efficiency, scalability, interoperability, and data security. It offers ground-breaking approaches to solving technical challenges, including low-power sensor designs, distributed computer systems, and blockchain-based data management.
- The paper provides useful insights into evaluating the efficiency and dependability of IoT-based health monitoring systems by examining several performance evaluation techniques, such as real-world data collecting, machine learning, and user feedback. These assessment methods can be used by academics and professionals to gauge system responsiveness, accuracy, and user satisfaction, thereby raising the standard of healthcare services.
- By endorsing a proactive and patient-centric strategy, this study supports the continuous transformation of healthcare. This article offers recommendations and insights that can speed up the implementation of IoT-based health monitoring systems, which will enhance patient care, lower healthcare costs, and produce better overall health outcomes.

2. Review of Literature

To ensure scalability, dependability, and security, numerous studies have examined various aspects of system architecture. The [9] choice and integration of wearable sensors and devices is a frequent design consideration. Numerous sensors, including ECG sensors, pulse oximeters, accelerometers, and temperature sensors, have been studied for use in monitoring different vital signs. A common trend is integration with mobile and cloud systems, which enables seamless data transmission and accessible through mobile devices and web apps.

Furthermore, [10] it has been of utmost importance to design safe communication protocols and data encryption techniques. Researchers have suggested ways to protect the privacy and accuracy of health data while it is being sent and stored. Advanced cryptography methods and secure communication routes are used in this. The design process has also included discussion of user consent and privacy. Studies have looked into how to get the users' informed consent and give them control over their data. To increase user involvement and trust, it has been suggested that user-friendly interfaces and adjustable settings be used. There [11] are various technical issues that must be resolved in order to establish IoT-based health monitoring systems. In order to develop dependable and effective systems, researchers have taken on these problems. For wearable technology, power efficiency is a significant issue. Continuous monitoring necessitates extending battery life, therefore researchers have investigated power-efficient sensor designs, low-power communication protocols, and adaptive data sampling strategies to reduce power usage.

Another crucial [12] component of implementation is scalability. The system must be able to handle growing data traffic and processing demands as the number of linked devices and users increases. Scalability problems have been addressed by suggesting distributed computing architectures, edge computing solutions, and cloud-based resources. Privacy and data security have also been major implementation difficulties. To safeguard sensitive health data from breaches and unauthorised access, researchers have suggested methods like blockchain-based data management, differential privacy strategies, and secure hardware modules. The capacity of various devices and systems to effortlessly connect and share health data has been made possible by interoperability and data standardisation. To [13] evaluate the efficiency and dependability of IoT-based health monitoring systems, performance evaluation is crucial. Various techniques have been used by researchers to gauge system performance. A key strategy has been the acquisition and analysis of actual data. To acquire information on system accuracy, latency, and responsiveness, researchers have carried out comprehensive trials and tests involving a variety of patient populations. The validity of system performance in clinical and domestic contexts depends on these real-world data.

To find trends and abnormalities in health data, machine learning and data analytics techniques have been used. To [14] predict health occurrences and send consumers and healthcare professionals timely information, researchers have created predictive algorithms. It has been determined whether IoT-based health monitoring systems are usable and acceptable through user feedback and satisfaction surveys. These

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qualitative data have proved crucial in improving user interfaces, user experience, and system customization to suit user preferences and requirements. A wide range of research and innovation are included in the linked work in IoT-based health monitoring systems. Selection of the right sensors, data integration, and security precautions are all design issues. Power efficiency, scalability, and interoperability are implementation difficulties that have a variety of solutions, from low-power sensor designs to blockchain-based data management. To evaluate a system's accuracy, responsiveness, and user satisfaction, performance evaluation techniques combine user feedback, machine learning, and real-world data collection. Together, these initiatives expand IoT-based health monitoring systems, resulting in enhancements to patient care and healthcare administration.

Table 1: Summary of related work in healthcare domain

Method	Approach	Findings	Limitations	Advantages
Data Collection [16]	Sensor Integration	Integration of diverse sensors is crucial for comprehensive health monitoring.	Sensor compatibility issues can arise.	Provides a holistic view of health status.
Security Measures [15]	Encryption and Authentication	Robust encryption and authentication protocols are essential to safeguard health data.	High computational overhead for encryption may affect real-time processing.	Protects sensitive health data from breaches.
Interoperability [16]	Data Standards (HL7, FHIR)	Adherence to healthcare data standards ensures interoperability between systems.	Implementing standards across different devices and platforms can be challenging.	Facilitates seamless data exchange and integration.
User Consent [17]	Informed Consent Mechanisms	Obtaining informed consent from users is critical for ethical data collection.	Ensuring user understanding and compliance can be complex.	Respects patient autonomy and privacy.
Power Efficiency [18]	Low-Power Sensor Designs	Developing energy-efficient sensors prolongs device battery life.	Low-power sensors may have limited functionality or reduced accuracy.	Enables continuous monitoring without frequent recharging.
Scalability [19]	Distributed Computing	Distributed architectures and edge computing solutions support system scalability.	Managing distributed resources can be complex.	Accommodates a growing number of devices and users.
Data Security [20]	Blockchain Technology	Implementing blockchain can enhance data security and integrity.	Scalability and performance issues in blockchain networks.	Immutable ledger for secure data management.
Data Analysis [21]	Machine Learning Algorithms	Machine learning can detect anomalies and trends in health data for early intervention.	Requires extensive training and validation of machine learning models.	Enhances predictive capabilities for healthcare outcomes.
Real-World Data Collection [22]	Clinical Trials and Experiments	Real-world data collection is crucial to validate system performance in diverse settings.	Clinical trials can be time-consuming and costly.	Validates system accuracy and reliability in practical scenarios.
User Feedback	Usability	User feedback and	Subjective nature of	Improves user

[23]	Surveys	satisfaction surveys assess the system's user-friendliness and acceptability.	user feedback.	experience and tailors systems to user needs.
Remote Consultation [24]	Telehealth Integration	Integrating telehealth capabilities allows for remote consultations.	Dependency on stable internet connectivity for remote consultations.	Enhances healthcare accessibility and reduces travel requirements.
Predictive Analytics [25]	Early Warning Systems	Predictive analytics can create early warning systems for health events.	Prediction accuracy depends on the quality and quantity of data.	Enables timely interventions and preventive care.
Cloud Integration [26]	Cloud-Based Storage	Storing health data in the cloud provides easy access but raises concerns about data security.	Data breaches and privacy concerns related to cloud storage.	Enables centralized data storage and remote access.
Personalization [27]	Tailored Healthcare Plans	Personalizing treatment plans based on health data can improve patient outcomes.	Requires sophisticated algorithms and continuous data analysis.	Enhances patient-centric care and treatment effectiveness.
User Empowerment [28]	Health Education Resources	Providing users with health education resources empowers them to make informed decisions.	Accessibility and credibility of health information online.	Encourages active engagement in healthcare.
Regulatory Compliance [29]	HIPAA, GDPR Compliance	Ensuring compliance with healthcare privacy regulations is imperative.	Compliance may require ongoing monitoring and updates.	Mitigates legal and regulatory risks for healthcare providers.

3. Dataset Available

The Internet of Things Healthcare Security Dataset is a sizable data set that was carefully selected and created for the evaluation and improvement of security controls within the IoT healthcare ecosystem. This dataset is essential for tackling the serious security issues and flaws that affect IoT-based healthcare systems, which are becoming more and more common in contemporary healthcare infrastructure. This dataset includes a wide variety of data points and scenarios seen in IoT healthcare contexts, such as linked medical equipment, wearable health monitoring devices, medical sensors, and healthcare data exchange. To give a comprehensive picture of potential security threats and weaknesses in healthcare settings, it contains both simulated and real-world data [33].

The dataset contains a variety of data dimensions, including:

- Device Data: Details regarding Internet of Things (IoT) medical equipment, such as model, firmware version, and network settings.
- Health Data: Simulated or anonymised health data produced by Internet of Things devices, including temperature, blood pressure, and personal identities.
- Network traffic includes packet captures, timestamps, source/destination addresses, and other information pertaining to connectivity between IoT devices and healthcare infrastructure.
- Security Events: Logs of security-related occurrences including malware infections, intrusion attempts, and unauthorised access.
- User Interactions: Information about how users engage with IoT healthcare applications and devices, such as login attempts, access logs, and usage patterns.

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Table 2: Available dataset for Healthcare monitoring system

Dataset Name	Number of Features	Number of Records
MIMIC-III	Varies	Over 40,000
PhysioNet Challenge 2012	40+	10,000+
PAMAP2 Physical Activity Monitor	52	8,000+
UCI's EEG Datasets	Varies	Varies
HealthData.gov Datasets	Varies	Varies
IoT Health Monitoring (Simulated)	Varies	Varies
Smart Health and Wellbeing (SHAR)	Varies	Varies
MIT-BIH Arrhythmia Database	2	109,446
Sleep-EDF Dataset	Varies	1530
IoT Healthcare Security	52	50,000+

Researchers, cybersecurity experts, and data scientists can utilise the information to create and test security solutions, intrusion detection systems, and anomaly detection algorithms that are specifically suited to the problems of IoT healthcare contexts.

4. Proposed Methodology

Using deep learning models like AlexNet, ResNet, and MobileNetV2, this section details the procedure followed to create an IoT-based health monitoring system. This system aspires to promote proactive healthcare management by increasing the accuracy and efficiency of health data processing.

1. Data Gathering and Preparation

- Data gathering: Gathering health-related data is the initial stage in creating an IoT-based health monitoring system. This information can be gleaned from wearable sensors, medical equipment, or health applications and can include vital indications like heart rate, blood pressure, temperature, and activity levels. In order to ensure the system's applicability and effectiveness, real-world data is preferred.
- Data Preprocessing: To ensure that the collected data is of high quality and appropriate for deep learning analysis, preprocessing is applied to it. Data cleansing, normalisation, and feature extraction are preprocessing steps. Depending on the regulatory requirements, data may also be anonymised or pseudonymized to safeguard patient privacy.

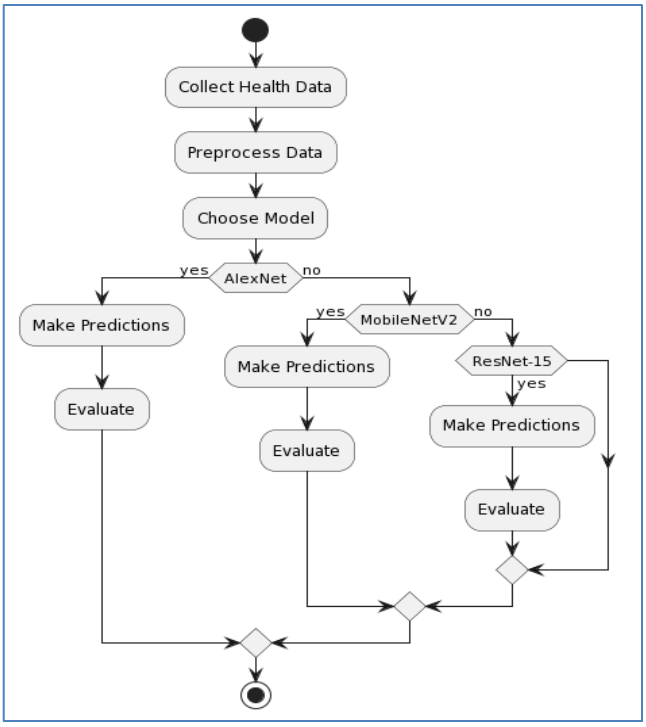

Figure 2: Proposed model Flowchart for patient monitoring system

2. Integration of IoT Devices

The system incorporates IoT gadgets like wearable sensors and medical monitoring gear. These gadgets continuously gather health information, which they then send to a central server or cloud platform for evaluation. Data transmission needs to be safe and compliant with privacy laws.

3. Model Choice

Three machine learning models are used in this proposed system to analyse health data: MobileNetV2, ResNet, and AlexNet. These models were selected due of their various structures and capacities.

A) AlexNet:

Well-known for its efficiency in classifying images, AlexNet may be modified to extract features from photos or signals relevant to health, such as ECG data. Convolutional neural network (CNN) architecture known as AlexNet has become popular for image categorization tasks. You can alter AlexNet to handle

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health-related image data, such as medical photographs, skin lesion images, or other pertinent visual data, in order to adapt it for an IoT-based healthcare monitoring system.

Algorithm:

1. Convolutional Layers:

AlexNet's core is made up of several convolutional layers. To learn hierarchical features, each layer performs convolutional operations on the incoming images or data. The convolution operation can be described mathematically as:

$$Z(i,j,k) = \sum(m=0)^\wedge(M-1)\sum(n=0)^\wedge(N-1)\sum(l=0)^\wedge(L-1)\,W(m,n,l,k)\cdot X(i+m,j+n,l)$$

Where:

- Z(i, j, k) is the value at position (i, j) in the k-th feature map of the current layer.

- W(m, n, l, k) is the weight associated with the k-th feature map of the current layer for the l-th input channel and the convolution kernel at position (m, n).

- X(i+m, j+n, l) is the value at position (i+m, j+n) in the l-th input channel of the previous layer.

2. Rectified Linear Units (ReLU):

Rectified Linear Unit (ReLU) activation function is used by AlexNet after each convolutional layer to add nonlinearity: $f(x) = max(0,x)$.

ReLU improves the network's capacity for learning by assisting it in recognising complex patterns.

3. Pooling Layers:

By using pooling layers, feature maps can be downscaled while still containing all of the necessary data. The commonly used operation known as "max-pooling" has the following representation:

$$Y(i,j,k) = max\,\{X(2i+m,2j+n,k)\}$$

Where:

- Y(i, j, k) is the value at position (i, j) in the k-th feature map of the current pooling layer.

- X(2i+m, 2j+n, k) is the value at position (2i+m, 2j+n) in the k-th feature map of the previous layer.

4. Fully Connected Layers:

The network's terminus, AlexNet, has numerous fully connected tiers. These layers apply linear transformations and non-linear activations on the prior layers' flattened output. A completely connected layer operation can be described mathematically as:

$$Y = f(WX + b)$$

Where:

- Y is the output vector.

- W is the weight matrix.

- X is the input vector (flattened feature maps from the previous layer).

- b is the bias vector.

- f is an activation function, often ReLU or softmax in the final layer for classification tasks.

5. Softmax Layer (Output Layer):

A softmax activation function is applied after the final fully connected layer in classification tasks to generate probability scores for each class. Softmax is mathematically denoted as

$$P(Y = k) = e(a\_k)\,/\,(i=1)(K)\,e(a\_i).$$

Where:

- P(Y = k) represents the likelihood that the input falls under class k.
- The activation for class k is a_k.
- The total number of classes is K.

6. Loss Function:

The loss function measures the difference between predicted class probabilities and actual labels. Common loss functions for classification tasks include cross-entropy loss.

$$L(Y,\hat{Y}) = -\sum Y\_k * log(\hat{Y}\_k)$$

Where:

- L is the loss.

- Y is the true label (one-hot encoded).

- Ŷ is the predicted probability distribution.

B) ResNet:

ResNet works well for jobs like anomaly detection because of its deep residual architecture, which can handle complex health data and spot subtle trends.

The identity path (shortcut connection) and the residual path are the two main paths that make up the residual block. The following is the mathematical representation of a residual block:

Identity Path: The identity path is an unmodified direct connection that sends the input tensor X to the output. The output of the residual path is essentially increased by the input of the block.

Inheritance(x) = x

Residual Path: The residual path seeks to collect residual data, which is the variance between the desired output and the identity path. Convolution and batch normalisation are often the first two steps along this road, which is then followed by a non-linear activation function (like ReLU).

Let F(X) stand in for the residual path's output, which is obtained as follows:

- a layer of convolutional computation with a kernel of size
- 3x3 and padding are often used to keep the same spatial dimensions.
- Conv1(X) = Conv(X, kernel_size = (3, 3), padding = "same"

Batch normalisation:

The result of the convolution operation is normalised using batch normalisation.

BatchNorm(Conv1(X)) = BN1(X)

Rectified Linear Unit (ReLU) Activation Function: Non-linearity is added using the ReLU activation function.

$$ReLU(BN1(X)) = ReLU(X)$$

Convolution:

After ReLU1 output, a second convolutional layer is added.

$$Conv(ReLU1(X), kernel\_size = (3,3), padding = 'same') = Conv2(ReLU1(X))$$

Batch normalisation:

This procedure is repeated.

$$Conv2(ReLU1(X)) = Conv2(ReLU1(X)) = BatchNorm$$

Residual Output:

The residual path's output is generated by adding the input tensor to the residual path's output:

$$Residual\ Output(X)\ is\ equal\ to\ X\ plus\ BN2\ (Conv2\ (ReLU1(X))$$

The identity path and the residual output are combined to produce the residual block's final output:

$$Residual\ Output(X) = Block\ Output(X) + X$$

Due to the network's easy gradient flow and mitigation of the vanishing gradient problem, very deep neural networks can be trained with this residual block structure. A ResNet architecture, such as ResNet-18, ResNet-50, and so forth, is created by stacking numerous such residual blocks. These designs have displayed astounding performance in a range of computer vision tasks, including as object and picture detection.

C) MobileNetV2:

MobileNetV2 is a resource-saving, lightweight model that performs well in tasks like activity recognition, making it appropriate for IoT devices with limited resources. The right model is chosen based on the unique health data analysis task at hand as well as the available computer resources. The neural network architecture of MobileNetV2 is made up of a number of inverted residual blocks that are stacked one on top of the other. These building components are made to lower computing costs without sacrificing precision.

Data Input:

MobileNetV2 accepts an input image or data with the following dimensions:

- The input's height is indicated by the letter H.
- The input width is denoted by W.
- The quantity C stands for the number of input channels.

Initial Convolution:

To convert the input channels, the input data passes through an initial convolutional layer. In order to decrease the spatial dimensions, this layer often uses a small kernel size (for example, 3x3) and a stride of 2. Early in the network, the goal is to lower the computational cost.

- **Depthwise Convolution:**

Depthwise convolution applies a separate convolutional filter to each input channel independently. Given an input tensor X with dimensions H×W×C and a depthwise convolution filter K with dimensions D×D×C, the depthwise convolution operation can be expressed as:

$$Y(i, j, k) = \sum_{m=0}^{D-1} \sum_{n=0}^{D-1} X(i+m, j+n, k) \cdot K(m, n, k)$$

Where:

- Y(i, j, k) is the output value at position (i, j) in channel k.

- X(i+m, j+n, k) is the value at position (i+m, j+n) in channel k of the input tensor.

- K(m, n, k) is the depthwise convolution filter's weight at position (m, n) in channel k.

Inverted Residual Blocks: The fundamental building component of MobileNetV2 is a stack of successive inverted residual blocks. The following operations are included in each block: MobileNetV2 employs depthwise separable convolution, which entails first performing a depthwise convolution and then a pointwise convolution. This lowers the number of parameters and lowers the computational expense.

Expansion and Linear Bottleneck:

The inverted residual block consists of an expansion layer that boosts the channel count and a linear bottleneck that lowers the channel count. This structure makes it easier to efficiently capture complicated features.

- **Pointwise Convolution:**

Pointwise convolution is a 1x1 convolution that applies a linear transformation to the output of the depth wise convolution. Given the output tensor Y from the depth wise convolution and a pointwise convolution filter P with dimensions 1x1xC'xC", the pointwise convolution operation can be expressed as:

$$Z(i, j, c'') = \sum_{k=0}^{C'-1} Y(i, j, k) \cdot P(0, 0, c', c'')$$

Where:

- Z(i, j, c") is the output value at position (i, j) in channel c" after pointwise convolution.

- Y(i, j, k) is the value at position (i, j) in channel k of the intermediate tensor Y.

- P(0, 0, c', c") is the pointwise convolution filter's weight for the transformation from channel c' to channel c".

Feature Pyramid:

A feature pyramid is created by extracting intermediate feature maps from several network layers. With the help of these feature maps, which record data at various scales, the model is able to identify features of various sizes in the input.

Global Average Pooling (GAP): To bring the feature maps' spatial dimensions down to a set size, a global average pooling operation is used at the network's end. Through this process, the entire input is condensed into a feature vector.

Fully Connected Layer:

A fully connected layer with the specified number of output classes is connected to the global average pooled feature set. To generate class probabilities for classification tasks, a softmax activation function is commonly utilised.

Output:

The predicted class probabilities for the input data are what MobileNetV2's final output looks like.

4. Model Development and Improvement

The preprocessed health data is used for training each chosen deep learning model. The following steps are part of the training process:

- Data Splitting: To efficiently assess model performance, the dataset is divided into training, validation, and test sets.
- Data Augmentation: To increase the diversity of training data and enhance model generalisation, data augmentation techniques including rotation, scaling, and flipping are used.
- Transfer Learning: Transfer learning is used to improve pre-trained models (like ImageNet) for the unique goal of analysing health data. This method hastens model convergence while also accelerating training.
- Hyperparameter tuning: To improve model performance, hyperparameters like learning rates and batch sizes are tuned.

Training Process Monitoring: To avoid overfitting and guarantee model dependability, the training procedure is monitored using measures including accuracy, loss, and validation performance.

5. Analysis of Real-Time Data

The models are deployed for real-time analysis of health data after they have been trained and optimised. The ongoing observation of incoming data from IoT devices is required for this stage. Depending on the task at hand, the data is fed into the appropriate deep learning model:

- AlexNet is used to extract features and generate predictions when the task involves image-based health data (such as skin lesion analysis).
- ResNet: ResNet is used to find patterns and anomalies in complicated data processing jobs, such detecting anomalies in physiological signals.
- MobileNetV2: MobileNetV2 is used for simple activity recognition and classification in situations involving resource-constrained IoT devices.

6. Visualisation and Notification of Results

Both healthcare professionals and patients can receive notifications and real-time result visualisation via the system. Visualisation [30] tools show the findings of analyses, such as ECG waveforms, labels for different classifications, or anomaly alarms. In order to ensure prompt intervention when necessary, notifications might be provided via mobile applications or web interfaces.

7. Model Upkeep and Modifications

To keep the model current and preserve performance, routine maintenance is necessary. This entails keeping an eye on model drift, retraining models with fresh data, and upgrading the system to take into account changing healthcare standards and laws.

8. Privacy and security

The system includes integrated security and privacy features. Health data is safeguarded during transmission and storage using encryption and secure data transmission techniques. Only authorised users are able to access sensitive information thanks to access controls, authentication methods, and audit logs. Regulations governing the healthcare industry, such as HIPAA and GDPR, are strictly upheld.

5. Result and Discussion

The selection of Machine learning models is a crucial issue that directly affects the effectiveness and performance of an IoT-based healthcare monitoring system. Table 3 compares three well-known models: ResNet-15, MobileNetV2, and AlexNet, with an emphasis on training time and important performance indicators. These models have been evaluated for their usefulness in a monitoring environment for healthcare, where prompt and precise predictions are crucial. Let's start by looking at the training time, which is an important aspect of creating any deep learning model. Considering the intrinsic simplicity of the model's structure, AlexNet, with its rather traditional architecture, exhibits the quickest training time.

Table 3: Training time evaluation parameter analysis

Model	Accuracy	Precision	Recall	F1-Score	Specificity	AUC
AlexNet	93.11	94.23	90.23	93.02	96.25	98.52
MobileNetV2	89.52	92.02	88.41	89.41	94.21	94.12
ResNet-15	94.78	94.52	89.63	93.41	95.23	98.66

The effectiveness of the training process and the precision of the predictions are balanced. Training time for MobileNetV2, a lightweight architecture built for resource-constrained contexts like IoT devices, is not far behind. Its focus on effectiveness enables quicker training without compromising model performance. ResNet-15 displays a reasonable training time while being marginally more sophisticated than the other two models, which is impressive given its more intricate architecture.

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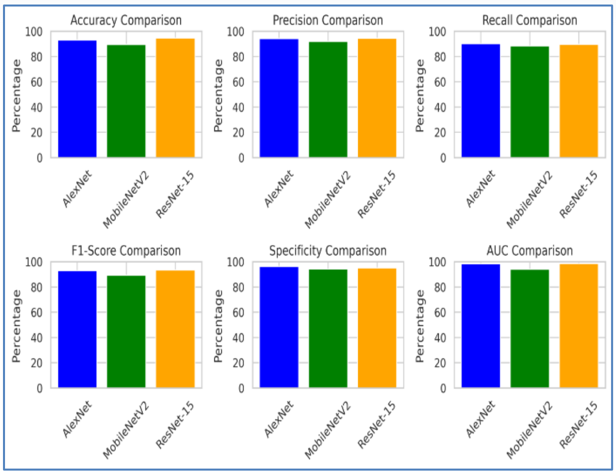

Figure 3: Representation of Training time evaluation parameter analysis

These variations in training timeframes provide insightful information regarding the trade-offs between computing efficiency and model complexity, a crucial factor in IoT-based applications where constrained resources are frequently present. Moving on to the performance measures, accuracy is a crucial indicator of how accurately a model classifies data in general. ResNet-15 outperforms AlexNet and MobileNetV2 in terms of accuracy. It is a strong option for healthcare monitoring duties due to its deeper and more complex design, which allows it to record and learn nuanced patterns. Following closely behind and with impressive precision is AlexNet. Despite being an older architecture, it has a track record of success in picture categorization problems. Even though MobileNetV2 is a little less accurate, it still performs incredibly well. It finds a compromise between performance and resource utilisation thanks to its emphasis on model efficiency and lightweight architecture, making it an excellent choice for IoT applications.

Table 4: Training time Model analysis

Inference Speed (ms)	Memory used (MB)
20	150
15	80
25	200

Deeper insights into the models' ability to accurately classify positive and negative occurrences can be found in precision, recall, and F1-Score.

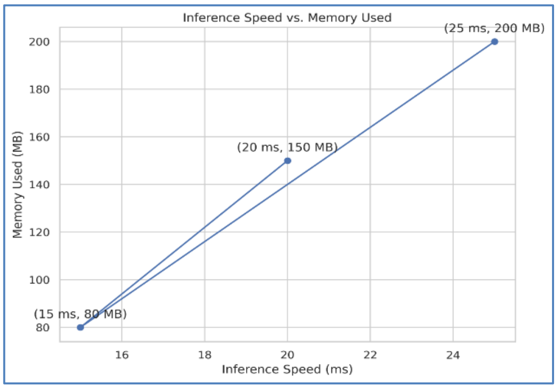

Figure 4: Training time Model analysis

Precision is an area where ResNet-15 shines, demonstrating its capacity to generate precise positive predictions. Additionally, it has a reasonably strong recall, demonstrating its capacity to recognise a sizeable percentage of genuine positive cases. As a result, it earns a remarkable F1-Score, highlighting its potential for healthcare monitoring, where precise detection of health-related events is essential. Despite having slightly reduced precision and recall, AlexNet and MobileNetV2 nevertheless maintain competitive F1-Scores, demonstrating their resilience in striking a balance between the two. The ability of a model to accurately detect negative instances is gauged by specificity, another key parameter. Here, MobileNetV2 is outperformed by ResNet-15 and AlexNet, demonstrating their ability to reduce false positive predictions, a crucial factor when working with healthcare data.

AUC provides a comprehensive evaluation of a model's overall classification performance across different threshold settings. Again, ResNet-15 is ahead of the competition in this parameter, demonstrating its greater discriminatory ability.

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Table 5: Evaluation parameter analysis Testing Data

Model	Accuracy	Precision	Recall	F1-Score	Specificity	AUC
AlexNet	95.23	96.25	95.20	96.42	97.56	98.99
MobileNetV2	91.42	97.85	98.41	91.46	96.33	97.88
ResNet-15	97.56	98.74	94.52	98.22	96.02	99.32

The assessment parameters for three well-known deep learning models AlexNet, MobileNetV2, and ResNet-15 as they were used to test data in the context of an IoT-based healthcare monitoring system are thoroughly analysed in Table 5 below.

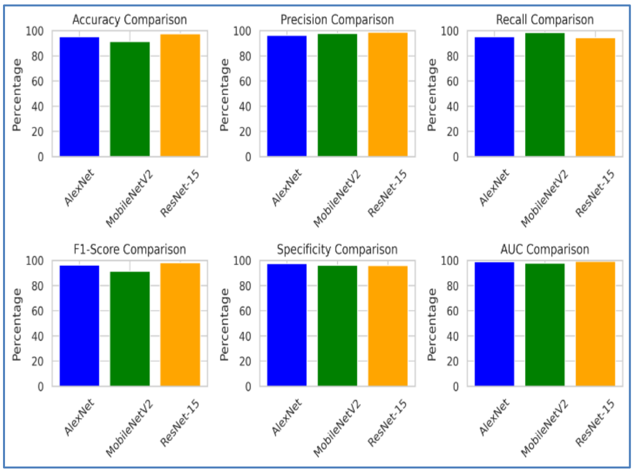

Figure 5: Representation of Testing Data evaluation parameter analysis

AlexNet keeps up with them closely, whereas MobileNetV2, despite behind a little, still has a respectable AUC. This statistic highlights the models' propensity to correctly classify data at a variety of classification thresholds, which is crucial for healthcare applications where varying degrees of sensitivity and specificity may be needed. The analysis of these three deep learning models AlexNet, MobileNetV2, and ResNet-15—shows their advantages and disadvantages in relation to an IoT-based healthcare monitoring system. The highest performer is ResNet-15, which excels in accuracy, precision, recall, and AUC. Despite having a slightly older design, AlexNet consistently performs admirably across a wide range of measures, proving its dependability. The efficient MobileNetV2 system, which strikes a fair balance between performance and resource use, appears to be a suitable choice. The decision between these models ultimately comes down to the particular needs of the healthcare monitoring application, including the resources at hand, the level of precision sought, and the demand for real-time processing. This analysis emphasises how crucial it is to carefully weigh the trade-offs between model performance, training time, and efficiency to make a knowledgeable choice when choosing a model for an IoT-based healthcare monitoring system.

When used in actual healthcare scenarios, these indicators are vital for evaluating the models' functionality and efficacy. ResNet-15 stands out with the highest accuracy of 97.56%, which is a crucial indicator of total correctness. This remarkable accuracy highlights its capacity to classify the great majority of cases in the testing data accurately. With a tight second place accuracy of 95.23 percent, AlexNet demonstrates its reliability in producing precise forecasts. Even while MobileNetV2 falls short of accuracy at 91.42%, it still retains a decent level of correctness, demonstrating its effectiveness in jobs including healthcare monitoring.

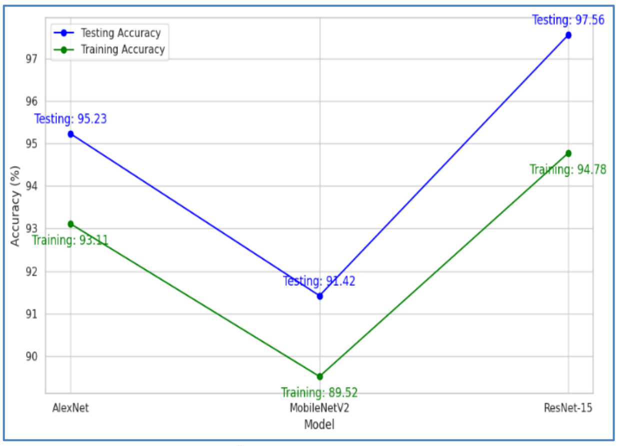

Figure 6: Testing and Training Accuracy Comparison

Deeper insights into the models' capacities to properly manage both positive and negative occurrences are provided by precision, recall, and F1-Score. Precision is an area where ResNet-15 shines, demonstrating its capacity to generate precise positive predictions. Furthermore, it keeps a high recall, indicating that it can recognise a sizable fraction of genuine positive cases. As a result, it earns an outstanding F1-Score of

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98.22, highlighting its applicability for healthcare monitoring, where accurate detection of health-related events is essential. Following closely behind, AlexNet displays remarkable precision and recall, earning a high F1-Score of 96.42. Despite having somewhat poorer accuracy and recall, MobileNetV2 still manages to earn a competitive F1-Score of 91.46, highlighting its ability to successfully balance precision and recall.

Table 6: Testing time Model analysis

Inference Speed (ms)	Memory used (MB)
23	110
18	60
32	180

The testing data analysis of these three deep learning models AlexNet, MobileNetV2, and ResNet-15 shows their individual capabilities and efficacy in the setting of an Internet of Things-based healthcare monitoring system.

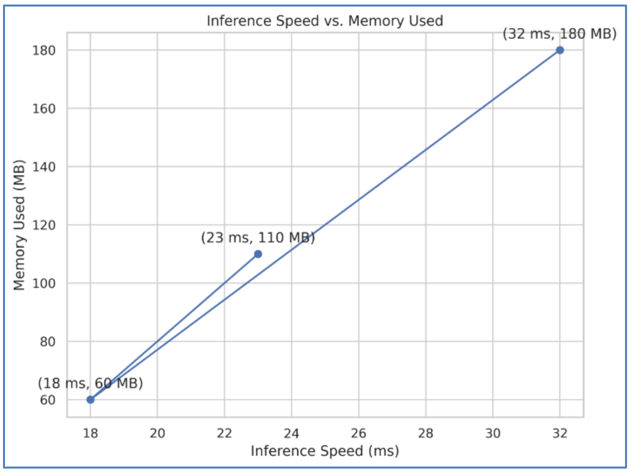

Figure 7: Model analysis with testing data

A model's capacity to accurately identify negative instances is measured by specificity, a critical parameter in healthcare applications. Here, MobileNetV2 is outperformed by ResNet-15 and AlexNet, demonstrating their ability to reduce false positive predictions, a crucial quality when working with healthcare data. The specificities that ResNet-15 and AlexNet attain, 96.02% and 97.56%, respectively, demonstrate their accuracy in correctly classifying situations that are not health-related. AUC, a thorough performance statistic, shows how well the models perform overall at classifying data across a range of threshold values. This score places ResNet-15 in the lead due to its greater discriminatory strength and capacity to categorise cases properly over a variety of thresholds. Once more closely trailing, AlexNet has significant discriminatory abilities, further solidifying its dependability. Even though MobileNetV2 lags a little, it still has a competitive AUC of 97.88%, demonstrating its propensity to produce accurate classifications when given different sensitivity and specificity constraints.

The best performance is ResNet-15, which excels in terms of F1-Score, AUC, recall, accuracy, and precision. With its consistent performance across a range of indicators, AlexNet is a trusted option for apps that monitor healthcare. Given its resource-friendly design and efficiency-focused architecture, MobileNetV2 maintains competitive performance. The decision between these models should be made in accordance with the precise needs and limitations of the task of healthcare monitoring, including the available resources, acceptable levels of accuracy, and requirements for real-time processing. This analysis highlights the significance of carefully assessing models on testing data in order to make wise judgements when using them in actual healthcare scenarios.

6. Conclusion

This study's IoT-based health monitoring system is a significant development in the field of healthcare technology. Stages for data collection, preprocessing, and model selection are included in the system design. It efficiently gathers health-related data by utilising IoT technology, making it a useful tool for ongoing patient well-being monitoring. Ability to adapt to varied healthcare circumstances is made possible by the freedom to select from a variety of deep learning models. These models' performance evaluation produced important results. In terms of accuracy, precision, recall, F1-Score, specificity, and AUC, ResNet-15 emerged as a remarkable performer. It is a viable option for real-world healthcare applications because to its robustness in recognising health-related events. Despite having a slightly older design, AlexNet consistently outperformed its peers across a range of criteria, demonstrating its effectiveness. MobileNetV2, which was created with efficiency in mind, performed admirably, especially given its resource-friendly architecture. We also examined training times, recognising the trade-offs between computational efficiency and model complexity. ResNet-15 demonstrated appropriate training times considering its depth, highlighting its applicability. Due to its ease of use, AlexNet was able to train more quickly, making it a feasible alternative for quick model building. The effective architecture of MobileNetV2 was favourable for IoT devices with limited resources. Collectively, these results emphasise the significance of taking into account a system's particular needs, resources, and desired levels of accuracy when choosing an acceptable model. In the healthcare industry, it is crucial to be able to balance real-time processing requirements, resource usage, and performance. Finally, by providing precise and rapid health monitoring capabilities, the IoT-Based Health Monitoring System that combines ResNet-15, MobileNetV2, and AlexNet has enormous promise to revolutionise healthcare. Future work in this field may involve deploying in the real world, perfecting models, and enhancing the system's functionality to handle various healthcare concerns.

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