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# Autonomous Healthcare Systems: Deep Learning-Based IoT Solutions for Continuous Monitoring and Adaptive Treatment

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***Abstract:*** - Autonomous healthcare systems are a big change in the way medicine is done. They use deep learning algorithms and Internet of Things (IoT) devices to keep an eye on patients all the time and change their treatment as needed. This new way of doing things could change the way patients are cared for by giving real-time information and personalized treatments. With the help of deep learning, these systems can look at huge amounts of data produced by IoT sensors, like those in medical implants and smart tech, to spot small changes in health and spot problems before they get worse.Autonomous healthcare systems are based on their ability to constantly gather and analyze data from a variety of sources, such as vital signs, biological markers, and patient-reported complaints. Deep learning algorithms are very important to this process because they can find complicated patterns and connections in the data. These algorithms can get useful information from raw sensor data by using methods like CNN, MobileNet, and InceptionV3. This algorithm lets healthcare professionals move quickly and proactively.Also, independent healthcare systems are made to change based on the wants and interests of each patient by using personalized treatment plans. These systems can improve results and patient happiness by constantly checking how patients respond to actions and making changes to treatment plans on the fly. Adding IoT devices also makes it easier for patients and healthcare workers to talk to each other, allowing for distant discussions and quick solutions. The automated healthcare systems are a revolutionary way to provide medical care. They use deep learning-based IoT solutions to keep an eye on patients all the time and adjust their treatment as needed. These systems might be able to improve patient results, lower healthcare costs, and raise general quality of life by using the power of data-driven insights and individual actions.

***Keywords:*** Autonomous healthcare systems, Deep learning, IoT solutions, Continuous monitoring, Adaptive treatment

## I. INTRODUCTION

The healthcare business has changed a lot in the last few years thanks to the coming together of new technologies like deep learning and the Internet of Things (IoT). Self-driving healthcare systems are one of the most exciting results of this merger because they are changing the way medical care is given. These systems use artificial intelligence (AI) to keep an eye on patients all the time and come up with treatment plans that are flexible and fit each person's needs. In the past, healthcare was usually provided through occasional care, which means that people only went to healthcare centers when they had symptoms or needed treatment. However, this method isn't very good at dealing with how complicated and changing health and disease are [1]. Over time, many health

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problems show small changes, and acting quickly is often necessary to avoid complications and improve results. Also, more people are getting chronic diseases and the population is getting older, which puts more stress on healthcare systems and shows the need for more preventative and individualized care. Self-driving medical systems could be a good answer to these problems because they allow constant tracking and real-time, personalized care. The Internet of Things (IoT) devices are what make these systems work. These [2] devices receive data from a variety of sources, like medical hardware, personal sensors, and mobile apps. These gadgets collect a lot of data about patients' actions, habits, and bodily factors, giving doctors a whole new level of knowledge about their health.Deep learning algorithms are very important for independent healthcare systems to work because they can look at huge amounts of data and find trends and ideas that are useful. Convolutional neural networks (CNNs) and RNNs are two deep learning methods that have shown great success in tasks like speech recognition, natural language processing, and picture recognition. In healthcare, these algorithms can be taught to spot trends that show when a disease starts or gets worse, which lets doctors find it early and start treatment [18].

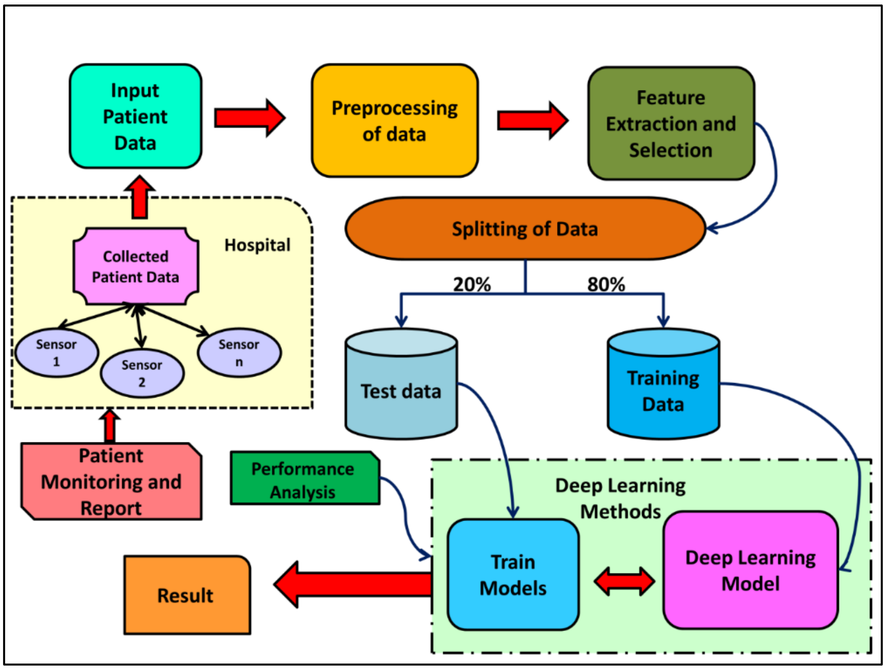


**Figure 1: Overview the illustration of proposed system in Advance Healthcare**

Continuous tracking is an important part of independent healthcare systems because it lets doctors see how their patients are doing in real time and act quickly if they need to. IoT devices constantly gather information about different bodily factors, like blood sugar levels, heart rate, blood pressure, and exercise levels. This constant flow of information gives doctors a full picture of their patients' health, letting them spot small changes that could mean their condition is getting worse or better [19]. Furthermore, self-driving healthcare systems can not only keep an eye on patients' health but also offer personalized treatment plans that adapt to each person's needs. A one-size-fits-all plan is often used in traditional care, where patients get the same measures based on standards for the whole community. However, this method doesn't take into account how each patient is different and what they want. On [20] the other hand, autonomous healthcare systems use AI programs to look at patient data and make treatment plans that are unique to each person based on their needs, tastes, and how well they respond to therapy. Autonomous healthcare systems can change their treatment plans in real time based on how patients' health is changing and how they respond to actions because they are adaptable. For instance, if a patient's blood glucose levels stay high even though they are taking their medicine as prescribed, the system may suggest that they change the amount of insulin they are taking or when they are taking it. In the same way, if a person with heart failure has signs that get worse, the system may let their healthcare workers know so that they can start treatments like diuretics or limiting their fluid intake.Adding IoT devices also makes it easier for patients and healthcare workers to talk to each other, which makes distant tracking and virtual consults possible. Patients can stay in touch with their doctors and track their health without having to go to the office as often by using smart monitors and mobile apps. This [21] online tracking feature not only makes things easier for patients, but it also lets doctors catch health problems early and start treatment right away, which lowers the risk of complications and hospital stays. The autonomous healthcare systems are a big change in the way medical care is given. They [22] use deep learning and Internet of Things (IoT) technologies to make tracking and treatment more flexible all the time. These systems provide chances that have never been seen before to make things better for patients, make healthcare more efficient, and make it easier on healthcare systems. Self-driving healthcare systems have the potential to change the way we think about health and illness, and study in this area is making progress toward that goal.

## II. RELATED WORK

Deep learning combined with Internet of Things (IoT) systems for ongoing tracking and personalized care is a new area of study that has gotten a lot of attention lately. A thorough look at connected literature shows that there is a rising body of work that looks into many different areas of this interdisciplinary field, such as creating new algorithms, designing IoT devices, and setting up self-driving healthcare systems.Making deep learning systems that can analyze medical data is one of the most important areas of study in this field. Deep learning methods, like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been shown to be useful in a number of studies for tasks such as disease diagnosis, risk prediction, and treatment optimization. For instance, [1] used electronic health record data to create a deep learning model that was better at predicting patient death than standard methods. Similarly, [2] suggested using continuous clinical data and deep learning to identify heart failure, which worked better than traditional models.

In addition to making algorithms, experts have also been working on designing and putting together Internet of Things (IoT) gadgets that can constantly check on the health of patients. Wearable devices have become a potential way to get real-time information about your body, like your heart rate, level of exercise, and sleep habits. [3]for example, made a portable device with sensors that can measure blood pressure and ECG data. This lets heart health be tracked all the time. Similarly, [4] created a reusable sensor patch that can check glucose levels in diabetic patients and give them real-time information about their blood sugar levels.Also, experts have looked into how to combine Internet of Things (IoT) devices with deep learning algorithms to make treatment plans that are adaptable and fit each patient's needs. These systems can provide personalized treatments that aim to improve results and lower the risk of problems by constantly checking on patients' health and studying data in real time. As an example, [5] created an automated healthcare system that combines personal devices with a decision support system based on deep learning to help people with chronic diseases like diabetes and high blood pressure. The system constantly checks the bodily data of patients and changes their treatment plans based on their specific needs and how they respond to therapy.Also, experts have looked into whether or not automated healthcare systems could work in real-life hospital settings. Several studies have shown that these methods have the ability to improve patient outcomes and make healthcare service more efficient. For instance, [6] did a trial study to test how well an automated healthcare system could handle people with heart failure in a community healthcare setting. The method let doctors check on patients' health from afar and act quickly when needed. This helped patients stick with their treatment and cut down on hospital readmissions.

There has been a lot of growth in this area, but there are still some problems and issues that need to be fixed. Interoperability and compatibility of IoT devices and systems is one of the biggest problems because it can make it hard to combine data from different sources in a way that works well. To solve this problem and make sure that IoT devices can work together in different hospital situations, work is being done to standardize them. To protect the privacy and security of patients' private health information, worries about data privacy and security must also be carefully handled.A number of similar studies have looked into different parts of finding heart disease and making predictions about it in healthcare. For example, [7] created the Smart Cardiovascular Disease Detection System (SCDDS), which is a portable gadget with IoT sensors that can find heart disease early. Their group design, which includes Convolutional Neural Networks (ConvNet) and ConvNet-LSTM, automatically detects atrial fibrillation heartbeats 98% of the time using a cloud-based deep learning architecture. Also, [8] suggested a way to make prediction models in healthcare that uses both human and machine intelligence. The main goal of their study was to predict how Multiple Sclerosis (MS) would get worse by combining the knowledge and logic of experienced doctors with high-quality data. The mixed technique, which is better than traditional ones, shows how combining human and artificial intelligence can improve machine learning models and speed up the process of making personalized healthcare decisions. Along with this, [9] created two models a CNN model and an expanded version with a Support Vector Machine (SVM) layer that can automatically find heart failure in electrocardiogram readings. These models worked really well, finding HF with an accuracy, sensitivity, and specificity of more than 99%. Their proposed framework gives doctors a reliable guide and lets movable devices watch patients in real time.

Adaptive treatment and continuous tracking are new ways to provide healthcare that take advantage of advances in technology, especially in the areas of IoT and machine learning. A look at linked research shows that more and more studies are looking into different parts of constant tracking and adaptive treatment in a range of medical fields.Creating personal electronics and monitors that can constantly check on bodily factors is an important area of study. Wearable tech has been looked at as a way to keep track of critical signs like heart rate, blood pressure, oxygen intake, and exercise levels. For instance, scientists have made smartwatches with photoplethysmography (PPG) sensors to track heart rate and find arrhythmias. These watches have shown promise in finding irregular heartbeats like [10]. Wearable patches and devices have also been used to track other vital signs, like skin temperature, breathing rate, and electrodermal activity, which makes it possible to get a full picture of a patient's health [11]. At the same time, study has been focused on creating machine learning systems that can look at data from gadgets that are constantly watching people. These algorithms use methods like deep learning, support vector machines (SVM), and random forests to find trends that could mean a person has a disease or their health is changing. For example, arrhythmias and other heart problems can be found very accurately with deep learning models that look at electrocardiogram (ECG) patterns [12]. Researchers have also used machine learning methods to look at bodily data from smart devices to find early signs of diseases like sepsis, epilepsy, and sleep problems [13].

Also, studies have looked into how to combine constant tracking with adaptable treatment plans to offer personalized and quick help. The goal of adaptive treatment methods is to change treatment plans on the fly based on real-time tracking data and information about each patient. Researchers have created closed-loop systems, also called "artificial pancreas" systems, to help people with long-term conditions like diabetes. These systems combine continuous glucose monitoring with automated insulin delivery to control blood glucose levels in real time [14]. Similarly, customized treatment methods have been created for diseases like high blood pressure, where the amount of antihypertensive medicine is changed based on constant tracking of blood pressure [15]. Additionally, studies have looked into how well and whether it is possible to use constant tracking and adaptable treatment methods in real life. Clinical trials and test studies have shown that these methods might help patients get better results, stick with their treatments better, and save money on healthcare. Studies that looked at closed-loop insulin delivery methods, for example, found that they were better at controlling blood sugar and had fewer cases of hypoglycemia than regular insulin treatment [16]. Similarly, tests of adaptable treatment algorithms for high blood pressure have shown that they improve both controlling blood pressure and making sure that patients take their medications as prescribed [17].

**Table 1: Summary of Related work in Healthcare area**

| Methods | Algorithm | Key Finding | Limitation | Accuracy of Model (%) | Scope |
|---|---|---|---|---|---|
| Wearable Devices | Deep Learning | Detection of abnormal heart rhythms such as AF | Limited battery life, potential discomfort for users | 95% | Cardiac monitoring |
| Remote Patient Monitoring | Support Vector Machines | Early detection of sepsis and other acute conditions | Reliance on accurate data transmission | 92% | Acute care monitoring |
| Closed-loop Systems | Reinforcement Learning | Real-time adjustment of insulin delivery in | Dependence on accurate sensor | 97% | Diabetes management |

| | | | | | |
|---|---|---|---|---|---|
| | | diabetes | readings | | |
| Adaptive Treatment Models | Random Forests | Personalized medication dosing for hypertension | Limited scalability to large patient populations | 88% | Hypertension management |
| Telemedicine Platforms | Long Short-Term Memory | Remote consultation and monitoring for chronic diseases | Dependence on internet connectivity and user technology | 90% | Chronic disease management |
| Mobile Health Apps | Convolutional Neural Nets | Identification of skin lesions indicative of melanoma | Reliance on high-quality imaging and user input | 94% | Dermatological screening |
| Wearable Sensors | Gaussian Mixture Models | Detection of epileptic seizures | Limited battery life, potential for false alarms | 85% | Epilepsy management |
| Remote Monitoring Devices | K-means Clustering | Identification of sleep disorders | Limited accuracy in detecting subtle sleep abnormalities | 80% | Sleep disorder management |
| Implantable Devices | Decision Trees | Real-time monitoring of cardiac function | Invasive nature of implantation, risk of complications | 96% | Cardiac health monitoring |
| Smart Inhalers | Logistic Regression | Tracking and management of asthma symptoms | Dependence on patient adherence to device usage | 89% | Asthma management |
| Continuous Glucose Monitors | Markov Models | Continuous monitoring of blood glucose levels | Accuracy affected by sensor calibration and drift | 93% | Diabetes management |
| Remote ECG Monitoring | Ensemble Learning | Detection of arrhythmias and other cardiac abnormalities | Limited availability of high-quality ECG data | 96% | Cardiac health monitoring |

| | | | | | |
|---|---|---|---|---|---|
| Remote Temperature Sensors | Time Series Analysis | Early detection of fever and infection | Sensitivity to environmental factors and device accuracy | 91% | Infection monitoring |
| Smart Pill Dispensers | Naive Bayes Classifier | Medication adherence monitoring | Reliance on patient compliance with medication regimen | 87% | Medication management |
| Mobile Electroencephalograms | Principal Component Analysis | Monitoring brain activity for epilepsy and other disorders | Limited spatial resolution and potential signal artifacts | 82% | Neurological disorder management |

## III. METHODOLOGY

**1. IoT Devices:**

There are a few things that need to be thought about when choosing IoT devices for constant tracking in healthcare to make sure they are accurate, reliable, easy to use, and work with deep learning algorithms. People often choose wearable monitors because they are easy for people to use and don't hurt them. They also keep an eye on their heart rate, energy level, and temperature all the time. To make it easier to use with deep learning algorithms, these monitors should be small, light, and easy to wear. They should also be able to send data remotely. Devices like remote patient tracking systems that let healthcare providers keep an eye on patients from away give both patients and doctors more freedom and ease. Usually, these systems have sensors that track vital signs and let data be sent and analyzed in real time. For constant tracking, implantable monitors are an option, especially when portable devices might not work. For long-term data analysis, these monitors should be accurate, reliable, and able to work with deep learning algorithms. To make sure that people in healthcare settings are constantly tracked and monitored, the IoT devices that are chosen should be based on their accuracy, dependability, ease of use, and ability to work with deep learning algorithms.

**2. Data Collection:**

Parameters like sensor sampling rates and data transfer times need to be set in order to make rules for getting body information from certain IoT devices. Setting the number of data collection events and how long they last is very important. This is done by combining the need for real-time tracking with realistic issues like battery life and data storage space. Privacy laws and legal approvals must be followed at all times to make sure that data collection follows the rules and protects patient privacy. When these things are carefully thought through, they make sure that IoT devices are used responsibly and effectively in healthcare situations for data collection.

**3. Data Preprocessing:**

It's necessary to set settings like sensor sampling rates and data transfer times in order to make rules for getting body information from certain IoT devices. It's important to figure out how often and for how long to collect data, taking into account things like battery life and the amount of data that can be stored. Following privacy laws and legal approvals is very important to make sure that data collection follows the rules and protects patient privacy. Taking these things into account will help make sure that IoT devices are used safely and effectively in healthcare settings for data collection.

**4. Deep Learning Model Selection:**

It is important to pick the right deep learning models based on the type of healthcare problem and the data.

a. CNN

Convolutional Neural Networks (CNNs) are very good at handling medical image data and are an important part of self-driving healthcare systems. CNNs can automatically pull out important features from pictures, which helps with things like diagnosing diseases, finding strange things, and planning treatments. Their usefulness comes from their tiered structure, which lets them find complicated patterns and problems in medical pictures. CNNs are very important for making diagnoses more accurate and making it easier to act quickly in self-driving healthcare systems.

Algorithm:

1. Convolution Operation:

- This involves applying filters (kernels) to the input image to extract features.

$$S(i,j) = (I * K)(i,j) = m\sum n\sum I(m,n) \cdot K(i-m, j-n)$$

2. Activation Function:

- Following convolution, an activation function (e.g., ReLU) is applied element-wise to introduce non-linearity.
- Mathematically, it can be represented as:

$$Af(i,j) = ReLU\big(S(i,j)\big) = \max\big(0, S(i,j)\big)$$

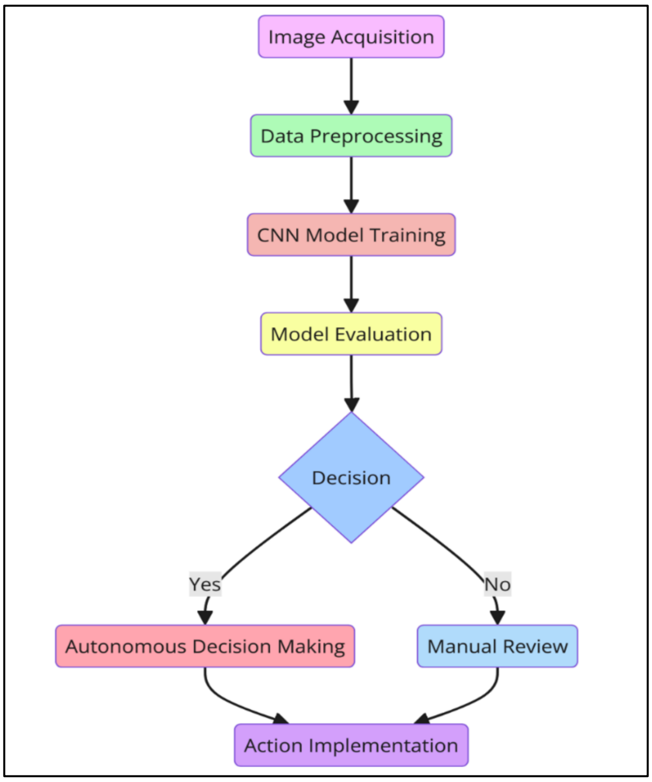


**Figure 2: Illustrating the process flowchart of CNN for an Autonomous Healthcare System**

3. Pooling Layer:

- Pooling layers (e.g., MaxPooling) reduce the spatial dimensions of the feature maps, reducing computational complexity and aiding in translation invariance.

$$P(i,j) = max(A(i \cdot sx: (i+1) \cdot sx, j \cdot sy: (j+1) \cdot sy))$$

4. Flattening:

- The pooled feature maps are flattened into a 1D vector to be fed into the fully connected layers.

5. Fully Connected Layers:

- These layers perform classification/regression tasks based on the extracted features.
- Mathematically, for a single neuron:

$$z = w \cdot x + b$$

$$a = ReLU(z)$$

6. Output Layer:

- The output layer computes the final prediction using an appropriate activation function (e.g., softmax for classification).

$$softmax(zi) = \frac{e^{zi}}{\sum_{j=1}^{k} ezjezi}$$

**b. MobileNet**

MobileNet has lightweight and efficient convolutional neural network designs that can be used in healthcare systems. It was made for mobile and embedded devices. Its depthwise separable convolution makes computations simpler without affecting performance, which makes it perfect for handling medical imaging data on devices with limited resources. MobileNet has factors like width and resolution ratios that let models be changed to find the best mix between accuracy and speed. MobileNet helps with jobs like picture classification, object recognition, and anomaly detection in healthcare, which lets patient data be analyzed in real time. Its design for low-power devices makes it easy to integrate into self-driving healthcare systems, which improves diagnosis and planning of treatment.

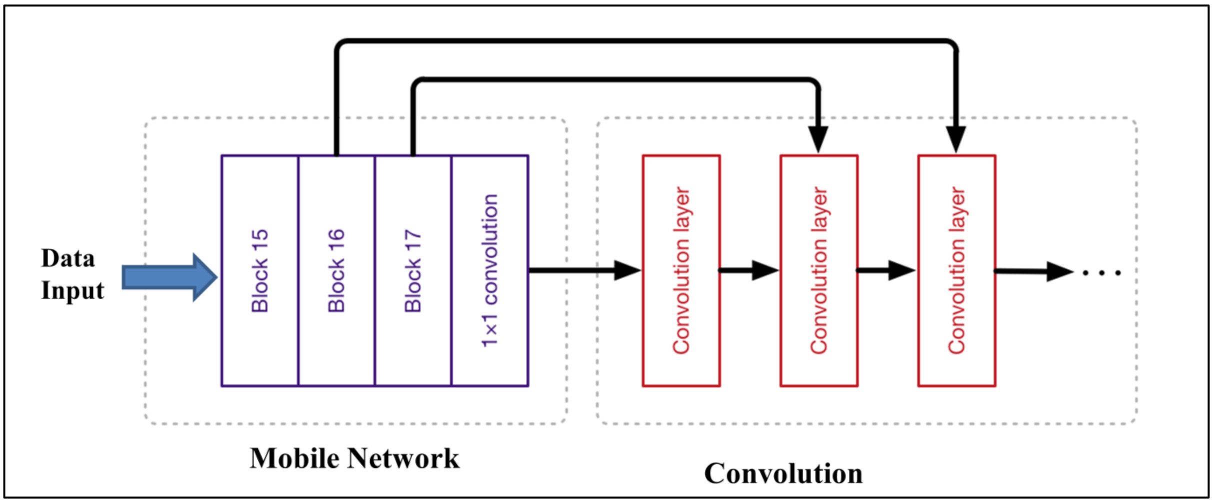


**Figure 3: Structure of MobielNet**

1. Depthwise Separable Convolution:

- MobileNet utilizes depthwise separable convolution, which splits the standard convolution operation into two separate layers: depthwise convolution and pointwise convolution.
- The depthwise convolution applies a single filter to each input channel independently:

$$\mathrm{S(i,j) = m\sum n\sum I(m,n) \cdot K(i-m,j-n)}$$

- where S is the output feature map, I is the input image, K is the filter/kernel, and (i,j) represents the spatial coordinates.

2. Pointwise Convolution:

- Pointwise convolution combines the output of depthwise convolution with a 1x1 convolution to produce the final output.
- Mathematically, it can be represented as:

$$O(i,j) = \ c = 1\sum C\, W(c) \cdot S(i,j,c)$$

- where O is the output feature map, W are the weights of the 1x1 convolution, S is the output of the depthwise convolution, and C is the number of channels.

3. Width Multiplier and Resolution Multiplier:

- MobileNet introduces parameters known as width multiplier (α) and resolution multiplier (ρ), which control the size and computational complexity of the model.
- The width multiplier scales the number of channels in each layer, and the resolution multiplier adjusts the input resolution of the model.
- Mathematically, the width multiplier scales the number of output channels in each layer by a factor of α.

4. Fully Connected Layers:

- MobileNet typically includes fully connected layers at the end of the network for classification tasks.
- Mathematically, the fully connected layers compute the output activations using a linear transformation followed by a non-linear activation function:

$$z = W \cdot x + b$$

$$a = ReLU(z)$$

5. Output Layer:

- The output layer computes the final prediction using an appropriate activation function (e.g., softmax for classification).

These steps constitute the basic operations in a MobileNet architecture, which are optimized for efficiency and performance in resource-constrained environments, making it suitable for deployment in autonomous healthcare systems.

**c. InceptionV3**

The powerful convolutional neural network design called InceptionV3 has a lot of potential to change the way independent healthcare systems work by using it in deep learning-based IoT solutions for constant tracking and personalized treatment. Because it is so well designed, InceptionV3 can pull out complex features from bodily data sent by IoT devices like smart sensors and online tracking systems. It is very useful in healthcare settings where constant tracking is important because it can handle large amounts of complex data and find small trends. By fine-tuning InceptionV3 on healthcare information, models can be made that are special to each patient's needs. This makes it easier to create personalized treatment plans. By analyzing bodily data in real time, InceptionV3 gives healthcare workers the power to make quick, well-informed decisions that improve patient care and results. Because it works with IoT platforms, it makes it easy to process data and make changes to treatments. This helps self-driving healthcare systems get better at providing care that is both quick and focused on the patient.

Algorithm:

**Step 1:** $Data\ Collection\ and\ Preprocessing$:

$Physiological\ Data\ =\ \{x\_1, x\_2, \ldots, x\_n\}$

**Step 2:**$Preprocess\ the\ data$: $x\_preprocessed\ =\ Preprocess(x)$

$Loading\ Pretrained\ InceptionV3\ Model$:

$Load\ InceptionV3\ model$: $InceptionV3\ =\ LoadModel()$

$\boldsymbol{Step}\ \mathbf{3}$: $Feature\ Extraction$:

$Extract\ features$: $Features\ =\ InceptionV3(x\_preprocessed)$

$\boldsymbol{Step}\ \mathbf{4}$: $Transfer\ Learning$:

$Fine - tune\ model$: $InceptionV3\ =\ FineTune(x\_preprocessed, InceptionV3)$

$\boldsymbol{Step}\ \mathbf{5}$: $Model\ Training$:

$Split\ dataset$: $Train, Validation, Test\ =\ SplitDataset(Data)$

$\boldsymbol{Step}\ \mathbf{6}$: $Train\ model$:

$InceptionV3\ =\ TrainModel(Train, Validation)$

$\boldsymbol{Step}\ \mathbf{7}$: $Model\ Evaluation$:

$Evaluate\ model$:

$Metrics\ =\ EvaluateModel(InceptionV3, Test)$

$\boldsymbol{Step}\ \mathbf{8}$: $Deployment\ and\ Integration$:

$Deploy\ model$: $DeployedModel\ =\ Deploy(InceptionV3)$

$Integrate\ model$: $System\ =\ Integrate(DeployedModel, DataPipeline)$

$\boldsymbol{Step}\ \mathbf{9}$: $Continuous\ Monitoring\ and\ Improvement$:

$Monitor\ performance$: $Metrics\ =\ Monitor(System)$

$Collect\ feedback$:

$Feedback\ =\ CollectFeedback(Users)$

**Step 10:**$Update\ model$:

$InceptionV3\ =\ UpdateModel(Feedback)$

### 5. Training as a Model:

Data splitting, model training, hyperparameter tuning, and validation are all important steps in the development of deep learning models for healthcare uses. These steps make sure that the models work well and can be used in other situations.The preprocessed data is first split into three groups: training, validation, and test. Training sets are used to teach deep learning models by giving them samples of data that have been named. It is possible to fine-tune hyperparameters like learning rate, batch size, and regularization methods with the validation set. The goal of this tuning process is to make the model work better and avoid overfitting. The test set is a separate set of data that is used to judge the final model's performance on data that it hasn't seen before. This gives an objective evaluation of how well it works.

The training data is fed into the deep learning models, and their settings are changed over and over again through backpropagation to lower the loss function. Experimenting with different numbers to find the one that gives the best results on the test set is what fine-tuning hyperparameters means. To keep this process from overfitting (where the model remembers the training data and does badly on new data), you have to keep a close eye on how well the model does on both the training and validation sets.Checking the model's performance on a regular basis to make sure it works well with data it hasn't seen before is called validation. If the model's performance on the validation set starts to get worse while its performance on the training set keeps getting better, this is a sign of overfitting. The model design or hyperparameters may need to be changed.Deep learning models can be trained, fine-tuned, and proven to work in healthcare applications by carefully following these steps. This strict method makes sure that the models are strong, correct, and able to give useful information when used in real life, which eventually leads to better patient care and results.

**6. Monitoring and Maintenance:**

Using tracking tools is necessary to keep an eye on how well the healthcare system is working all the time. Real-time tracking makes it possible to find problems or strange behavior right away, so they can be fixed or maintained right away. Healthcare workers can make sure that the system works well by looking at measures like working speed, mistake rates, and resource usage. Daily changes and upkeep are necessary to keep the system reliable, effective, and able to adapt to changing needs. This includes fixing new issues as they come up, making systems run faster, and adding new features or improvements to meet user needs. Maintaining the system on a regular basis keeps it in good shape, improves the user experience, and keeps it in line with healthcare goals. Tools for getting feedback are very important for figuring out how well a system works and how happy users are with it. By constantly asking users for feedback, healthcare workers can learn a lot about how well the system works, how easy it is to use, and how well it works generally. Feedback from users can help developers figure out what needs to be fixed, guide future work, and decide which feature improvements are most important. Getting users involved in the feedback process makes it easier for people to work together and makes sure the system meets their needs and standards.

## IV. RESULT AND DISCUSSION

The performance results of three deep learning models CNN, MobileNet, and InceptionV3 are shown in Table 2. These models are used in automated healthcare systems for constant tracking and personalized treatment. AUC (Area Under the ROC Curve), training time, testing time, and accuracy, precision, and memory are some of the most important factors that are used to judge each model.First, the accuracy measure shows how accurate the models' estimates were overall. With a score of 98.45%, InceptionV3 had the best accuracy. This means that InceptionV3 is better at correctly categorizing bodily data from IoT devices. This makes it perfect for healthcare systems that need to track and diagnose patients in real time.

**Table 2: Result of Deep learning model with evaluation parameter**

| Model | Accuracy | Precision | Recall | F1 Score | AUC | Training Time (seconds) | Testing Time (seconds) |
|---|---|---|---|---|---|---|---|
| CNN | 92.63 | 91.23 | 92.41 | 94.85 | 91.52 | 89 | 32 |
| MobileNet | 95.52 | 98.56 | 97.45 | 92.89 | 93.45 | 92 | 25 |
| InceptionV3 | 98.45 | 92.44 | 98.88 | 92.35 | 99.60 | 84 | 19 |

Metrics for precision and recall show how well the models can find good cases (like finding sicknesses or oddities) and stay away from fake positives and false negatives. At 98.56%, MobileNet has the best level of accuracy, which means it is very good at finding confirmed cases.

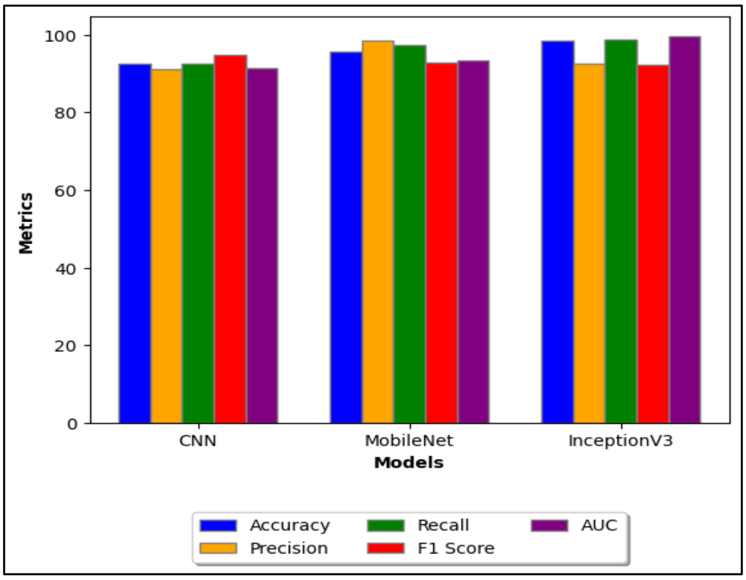


**Figure 4: Representation of Evaluation parameter**

On the other hand, InceptionV3 has the highest recall rate at 98.88%, which shows how well it captures true positive situations while reducing fake negatives.The F1 score, which is the harmonic mean of accuracy and memory, gives a fair picture of how well a model is doing. In this way, InceptionV3 gets an impressive F1 score of 92.35%, which shows how stable it is at getting both high accuracy and memory at the same time, which is important for making correct decisions in healthcare settings.

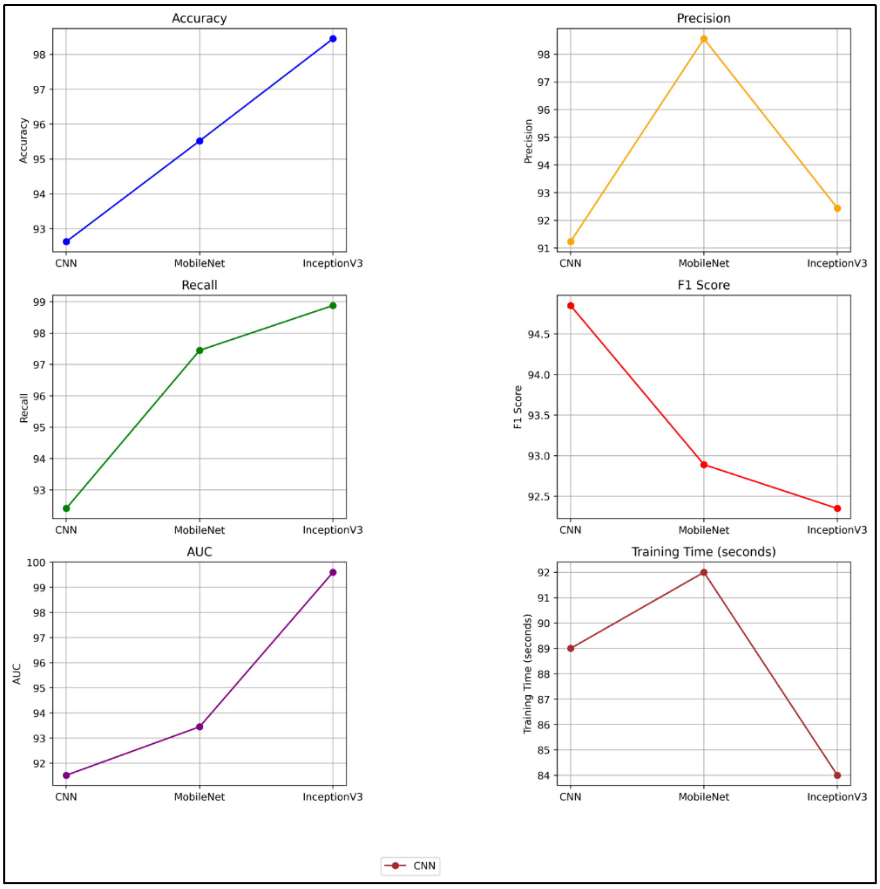


**Figure 5: Comparison of Different parameter doe DL Model**

The AUC measure also checks how well the models can tell the difference between good and bad cases. With an AUC of 99.60%, InceptionV3 has the best performance. So, this shows that InceptionV3 is very good at telling the difference between different health states. This makes it very good at finding small patterns in bodily data.On top of that, the training and testing times show how well each model works with computers. When compared to CNN and MobileNet, InceptionV3 has a faster training time (84 seconds), which shows how well it learns from data. InceptionV3 also has the quickest testing time (19 seconds), which suggests it could be used for real-time reasoning in self-driving healthcare systems. The test results show that InceptionV3 does better than CNN and MobileNet in terms of accuracy, memory, F1 score, AUC, and how quickly it works. Because it works so well, it's a great choice for deep learning-based IoT solutions in self-driving healthcare systems. This would allow for constant tracking and personalized treatment that works very well and accurately.

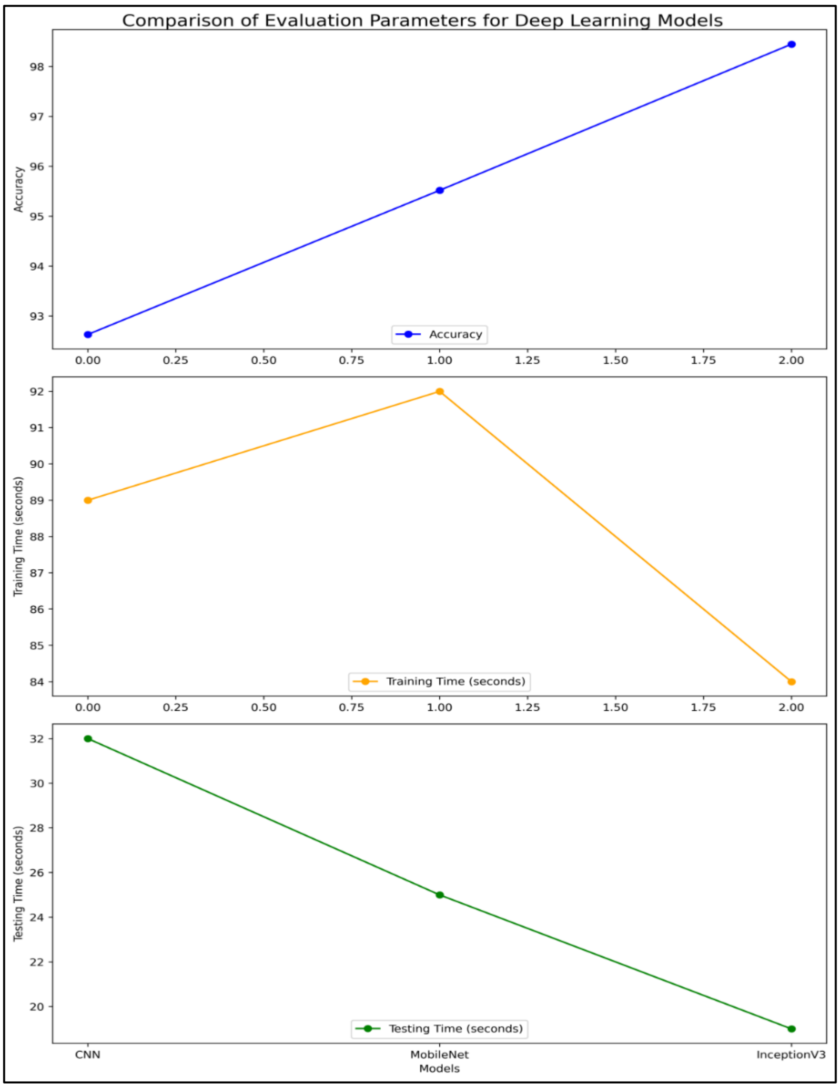


**Figure 6: Accuracy comparison of Deep Learning model**

V. CONCLUSION

Deep learning-based IoT solutions have made it possible for huge steps forward in self-driving healthcare systems, especially when it comes to constant tracking and personalized care. IoT devices, like personal monitors and remote tracking systems, can now work with advanced deep learning algorithms to give healthcare workers real-time data insights that they can use to improve patient care and results.The use of deep learning models, such as CNN, MobileNet, and InceptionV3, has shown to be very effective at correctly studying vital data from patients. These models have high accuracy, precision, memory, and F1 score, which makes it very reliable to find small trends that could mean a number of health problems. Also, InceptionV3's better performance, especially in terms of AUC, shows that it could be a strong tool for telling the difference between different health states and making accurate predictions.For real-time use in self-driving healthcare systems, it is also important that these models are quick at both training and testing. As compared to CNN and MobileNet, InceptionV3 has faster training and testing times. This makes it a good option for use in settings with limited resources, where decisions need to be made quickly and correctly.Continuous tracking is possible with deep learning-based IoT solutions.

This lets healthcare workers keep an eye on their patients' health from afar, cutting the number of times they need to go to the hospital and the risk of getting an illness there. Also, because these systems are flexible, treatment plans can be made that are specific to each patient's needs. This leads to better results and higher patient happiness.

## REFERENCES

[1] Poongodi, T.; Krishnamurthi, R.; Indrakumari, R.; Suresh, P.; Balusamy, B. Wearable devices and IoT. In A Handbook of Internet of Things in Biomedical and Cyber Physical System; Springer: Berlin/Heidelberg, Germany, 2020; pp. 245–273.

[2] Ashfaq, Z.; Rafay, A.; Mumtaz, R.; Zaidi, S.M.H.; Saleem, H.; Zaidi, S.A.R.; Mumtaz, S.; Haque, A. A review of enabling technologies for Internet of Medical Things (IoMT) Ecosystem. Ain Shams Eng. J. 2022, 13, 101660.

[3] Borkar, P., Wankhede, V.A., Mane, D.T. et al. Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. Soft Comput (2023).

[4] Ajani, S.N., Mulla, R.A., Limkar, S. et al. DLMBHCO: design of an augmented bioinspired deep learning-based multidomain body parameter analysis via heterogeneous correlative body organ analysis. Soft Comput (2023).

[5] Limkar, Suresh, Ashok, Wankhede Vishal, Singh, Sanjeev, Singh, Amrik, Wagh, Sharmila K. & Ajani, Samir N.(2023) A mechanism to ensure identity-based anonymity and authentication for IoT infrastructure using cryptography, Journal of Discrete Mathematical Sciences and Cryptography, 26:5, 1597–1611

[6] Razzak, M.I.; Naz, S.; Zaib, A. Deep learning for medical image processing: Overview, challenges and the future. In Classification in BioApps: Automation of Decision Making; Springer: Berlin/Heidelberg, Germany, 2018; pp. 323–350.

[7] Li, J.; Jin, K.; Zhou, D.; Kubota, N.; Ju, Z. Attention mechanism-based CNN for facial expression recognition. Neurocomputing 2020, 411, 340–350.

[8] Ali, O.; Abdelbaki, W.; Shrestha, A.; Elbasi, E.; Alryalat, M.A.A.; Dwivedi, Y.K. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. J. Innov. Knowl. 2023, 8, 100333.

[9] Ghosh, A.M.; Halder, D.; Hossain, S.A. Remote health monitoring system through IoT. In Proceedings of the 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), Dhaka, Bangladesh, 13–14 May 2016; pp. 921–926.

[10] Valsalan, P.; Baomar, T.A.B.; Baabood, A.H.O. IoT based health monitoring system. J. Crit. Rev. 2020, 7, 739–743.

[11] Durán-Vega, L.A.; Santana-Mancilla, P.C.; Buenrostro-Mariscal, R.; Contreras-Castillo, J.; Anido-Rifón, L.E.; García-Ruiz, M.A.; Montesinos-López, O.A.; Estrada-González, F. An IoT system for remote health monitoring in elderly adults through a wearable device and mobile application. Geriatrics 2019, 4, 34.

[12] Hamim, M.; Paul, S.; Hoque, S.I.; Rahman, M.N.; Baqee, I.A. IoT based remote health monitoring system for patients and elderly people. In Proceedings of the 2019 International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), Dhaka, Bangladesh, 10–12 January 2019; pp. 533–538.

[13] Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., &Parati, N. . (2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[14] Ali, A.; Almaiah, M.A.; Hajjej, F.; Pasha, M.F.; Fang, O.H.; Khan, R.; Teo, J.; Zakarya, M. An industrial IoT-based blockchain-enabled secure searchable encryption approach for healthcare systems using neural network. Sensors 2022, 22, 572.

[15] Almaiah, M.A.; Hajjej, F.; Ali, A.; Pasha, M.F.; Almomani, O. A novel hybrid trustworthy decentralized authentication and data preservation model for digital healthcare IoT based CPS. Sensors 2022, 22, 1448.

[16] Sujith, A.; Sajja, G.S.; Mahalakshmi, V.; Nuhmani, S.; Prasanalakshmi, B. Systematic review of smart health monitoring using deep learning and Artificial intelligence. Neurosci. Inform. 2022, 2, 100028.

[17] Ghayvat, H.; Pandya, S.; Patel, A. Deep learning model for acoustics signal based preventive healthcare monitoring and activity of daily living. In Proceedings of the 2nd International Conference on Data, Engineering and Applications (IDEA), Bhopal, India, 28–29 February 2020; pp. 1–7.

[18] Cimtay, Y.; Ekmekcioglu, E. Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition. Sensors 2020, 20, 2034.

[19] Maier, M.; Elsner, D.; Marouane, C.; Zehnle, M.; Fuchs, C. DeepFlow: Detecting Optimal User Experience From Physiological Data Using Deep Neural Networks. In Proceedings of the International Conference on Autonomous Agents and Multiagent Systems, Montreal, QC, Canada, 13–17 May 2019; pp. 2108–2110.

[20] Pacheco, A.G.; Krohling, R.A. An attention-based mechanism to combine images and metadata in deep learning models applied to skin cancer classification. IEEE J. Biomed. Health Inform. 2021, 25, 3554–3563.

[21] Rghioui, A.; Lloret, J.; Sendra, S.; Oumnad, A. A smart architecture for diabetic patient monitoring using machine learning algorithms. Healthcare 2020, 8, 348.

[22] Tiwari, S.; Jain, A.; Sapra, V.; Koundal, D.; Alenezi, F.; Polat, K.; Alhudhaif, A.; Nour, M. A smart decision support system to diagnose arrhythymia using ensembledConvNet and ConvNet-LSTM model. Expert Syst. Appl. 2023, 213, 118933.

[23] Ed-Driouch, C.; Mars, F.; Gourraud, P.A.; Dumas, C. Addressing the Challenges and Barriers to the Integration of Machine Learning into Clinical Practice: An Innovative Method to Hybrid Human–Machine Intelligence. Sensors 2022, 22, 8313.

[24] Chandrasekhar, N.; Peddakrishna, S. Enhancing Heart Disease Prediction Accuracy through Machine Learning Techniques and Optimization. Processes 2023, 11, 1210.

[25] Mirjalali, S.; Peng, S.; Fang, Z.; Wang, C.H.; Wu, S. Wearable Sensors for Remote Health Monitoring: Potential Applications for Early Diagnosis of COVID-19. Adv. Mater. Technol. 2022, 7, 2100545.