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An Intelligent IoT Framework for Personalized Healthcare: Integrating Machine Learning Algorithms for Real-time Patient Monitoring and Diagnosis

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Abstract: The Internet of Things (IoT) has changed healthcare by letting doctors keep an eye on patients in real time and give them more personalized care. We present an Intelligent IoT Framework for Personalized Healthcare (IIFPH) in this study. It includes machine learning (ML) methods for diagnosing and tracking patients in real time. IoT devices, like medical tools and monitors that can be worn, are used by the framework to constantly gather data about patients. The information is then sent to a central computer site to be analyzed and processed. The IIFPH uses machine learning techniques, such as deep learning and ensemble methods, to look at the data and figure out how healthy the patient is. To make sure the results are accurate and reliable, these algorithms are taught using a wide range of datasets. The structure also has a unique suggestion system that gives each patient individualized medical care based on their health history and personality. Its ability to provide real-time tracking and analysis is one of its most important features. This lets healthcare workers act quickly if anything goes wrong. Encryption methods and access rules built into the system also protect data privacy and security. To find out how well the proposed framework worked, we used real patient data in a number of studies. The data show that the IIFPH can correctly track and identify a wide range of health problems, from short-term illnesses to long-term ones. The suggested approach could, in general, improve the standard of healthcare services and the results for patients in personalized healthcare situations.

Keyword: *IoT, Machine Learning, Patient Monitoring, Healthcare, Personalized Care*

1. Introduction

In the past few years, there has been a big change in the healthcare business toward more specialized and effective care for patients. Adding machine learning methods to healthcare systems is a key part of this change, especially when it comes to diagnosing and tracking patients in real time. A type of AI called machine learning has a huge amount of promise for looking at complicated healthcare data and finding insights that can be used to make things better for patients. This essay looks at how machine learning methods have changed real-time patient tracking and analysis. It talks about their uses, problems, and possible futures [1]. Algorithms for machine learning are made to learn from data, find trends, and make choices or guesses without being told to do so. In healthcare, these algorithms can look at different kinds of data, like vital signs, medical pictures, genetic data, and patient records, and pull out useful information. Using this information,[2] machine learning systems can help doctors figure out what diseases patients have, guess how they will do, and make personalized treatment plans. Real-time patient tracking is one of the most important ways that machine learning is used in healthcare. Regular checks and physical help are common parts of traditional tracking methods, but they might miss quick changes in a patient's state. When combined with Internet of Things (IoT) [3] devices, machine learning techniques make it possible to keep an eye on patients all the time. These programs can look at live data from monitors, smart tech, and medical gear to find trends or outliers that could point to health problems. Real-time tracking can help stop bad things from happening and make it easier to act quickly by sending early signs.

Disease detection is [4] another important way that machine learning is used in healthcare. Medical pictures like X-rays, MRIs, and CT scans can be analyzed by machine learning techniques that help doctors find problems or diagnose specific conditions. On top of that, these programs can look at clinical data like symptoms, medical background, and lab reports to help doctors make correct decisions. Machine learning can improve the accuracy and speed of diagnoses, especially for rare or complicated diseases, by adding computer analysis to

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human knowledge. There are some problems with adding machine learning methods to healthcare systems, even though they could be helpful. For teaching and verifying algorithms, one of the biggest problems is getting good data that has been tagged. It can be hard to get and mark healthcare data because it is often broken up, incomplete, and private. Also, keeping patient data private and safe is very important, which needs strong data control systems and following the rules set by regulators. Also, [5] it's still not clear how machine learning systems work, which is especially important when making important healthcare decisions. Even though these algorithms can make accurate predictions, it is important for healthcare workers and patients to understand the reasoning or factors that affect the forecasts in order to trust and accept them. The machine learning systems could change the way healthcare professionals diagnose and watch over patients in real time. These programs can give useful information, make diagnoses more accurate, and improve patient results by using the huge amounts of data that are created in healthcare situations. Getting rid of problems with data quality, safety, and readability is important for getting the most out of machine learning in healthcare [6].

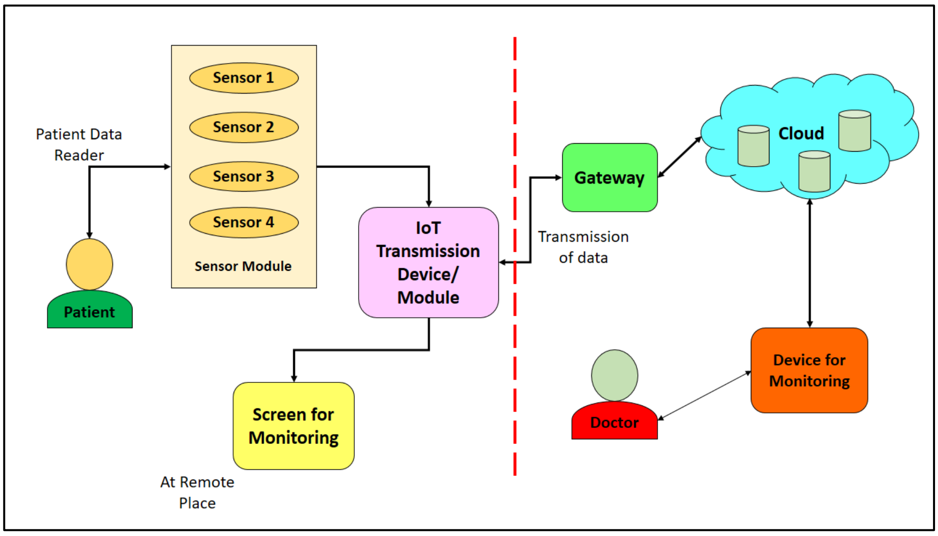

Fig 1: Overview of patient Monitoring system

Personalized healthcare tries to make medical care fit the unique traits of each person, like their genes, habits, and the surroundings they live in. By using IoT devices like smart medical devices, personal monitors, and online tracking systems, healthcare workers can get data from patients all the time. This information includes vital signs, amounts of exercise, drug adherence, and external factors, giving a full picture of a person's health. This study [7] shows an IoT system that combines these different types of data streams and uses machine learning techniques to look at the data and figure out what it all means. Machine learning systems can look at data and find patterns, outliers, and trends. This lets doctors make smart choices and tailor treatments to each patient's needs. For instance, these algorithms can tell when chronic diseases like diabetes or high blood pressure will start by looking at changes in vital signs and living factors. This lets doctors start treating the disease early and stop it from happening. One of the best things about the IoT system for personalized healthcare is that it can help patients become more involved and take better care of themselves. Internet of Things (IoT) gadgets give people control over their own health by giving them access to their health data and comments in real time. Wearable tech can, for example, tell people to take their medicines, keep track of how much they exercise, and give them information about their general health and well-being. By allowing online tracking and medical services, the IoT system [8] can also make healthcare more efficient and lower costs. Healthcare professionals can check on patients' health from afar, so they don't have to go to the hospital as often and can act quickly when needed. The structure can also make it easier for healthcare workers to talk to each other and share data, which can improve care management and cut down on medical mistakes. Even with these benefits, using IoT in healthcare comes with some problems, such as worries about data safety and security, problems with connectivity, and the need to follow rules. Making sure that patient data is kept private and correct is important for getting patients and healthcare workers to trust and accept it. Also, making sure that different IoT systems and devices can talk to each other is very important for smooth data transfer and interaction.

2. Related Work

A lot of study and development has gone into real-time patient tracking and analysis over the past few years, with a focus on using advanced technologies like the Internet of Things (IoT), machine learning, and artificial intelligence (AI). This part talks about some of the most important study efforts and changes in this area. It shows the progress, the problems, and the possible future paths. Wearable gadgets that continuously track a patient's health are one of the most innovative ways to keep an eye on them in real time. [9] for example, showed that it is possible to use a wearable sensor system to continuously check critical signs like heart rate, blood pressure, and oxygen levels. Machine learning techniques were built into the system to look at the data and find trends that didn't make sense, which could be signs of health problems. In the same way, [10] used machine learning to create a portable sensor device for older patients that can identify falls and recognize activities.

A lot of study has been done on how to build and set up IoT platforms for real-time patient tracking in order to connect healthcare systems to the internet of things. For example, [11] suggested using the Internet of Things (IoT) to keep an eye on people who have long-term illnesses like diabetes and high blood pressure. IoT devices were used to collect data on patients' vital signs and how well they took their medications. Machine learning systems then used that data to make personalized suggestions for how to handle the disease. A lot of machine learning techniques have also been used to diagnose and keep an eye on patients in real time. For instance, [12] used data from electronic health records and bodily monitors to create a machine learning-based system that can tell when a hospital patient is getting worse. The system was very good at predicting bad things that would happen, showing that machine learning can help improve patient results. Adding medical image data is another important part of watching patients in real time. New developments in AI and deep learning have made it possible to create programs that can instantly look at medical pictures like X-rays, MRIs, and CT scans and figure out what's wrong. [13] for example, made a deep learning system that can identify pictures of skin cancer just as well as doctors can.

AI and machine learning have also been used to make disease diagnosis more accurate and faster, in addition to real-time tracking. For instance, [14] showed that deep learning could be used to diagnose diabetic retinopathy, getting very good results in finding the disease in retinal pictures. In the same way, [15] created a deep learning system that could diagnose pneumonia from chest X-rays, sometimes better than doctors. Real-time patient tracking and analysis have come a long way, but there are still some problems that need to be solved. Bringing together different data sources and forms is one of the biggest problems. To solve this, we need communication guidelines and data merging methods. Also, keeping patient data private and safe is very important, which means strong data protection and access control systems are needed, Also, AI and machine learning systems are still hard to understand, which is a big problem, especially in healthcare situations where trust and openness are very important. The technologies like IoT, machine learning, and AI have made big steps forward in real-time patient tracking and analysis. These tools have made it possible to keep an eye on patients all the time, find health problems early, and make personalized care plans. To get the most out of real-time patient tracking and analysis for better patient results and healthcare delivery, however, problems with data merging, privacy, and readability must be solved.

Table 1: Summary of Related work

Method	Dataset Used	Key Finding	Limitation	Scope
Wearable Sensors [16]	Physiological data	Continuous monitoring of vital signs such as heart rate, blood pressure, and oxygen saturation.	Limited battery life of wearable devices, potential discomfort for patients wearing them continuously.	Potential for remote monitoring of patients in real-time, early detection of health issues.
IoT Framework [17]	Chronic disease patients	IoT devices for data collection on vital signs, medication adherence. Machine learning for personalized disease management.	Dependency on reliable internet connectivity for data transmission, data privacy concerns.	Improved disease management for chronic patients, potential for reducing healthcare costs.
Machine Learning [18]	Electronic health records	Predicting patient deterioration in hospital settings, achieving high accuracy in predicting adverse events.	Dependency on quality and availability of electronic health records, potential bias in algorithm predictions.	Early prediction of adverse events, potential for improving patient outcomes in hospital settings.

AI and Deep Learning [19]	Medical imaging (X-rays,	Deep learning for analyzing medical images in real time, achieving high sensitivity and specificity in disease detection.	Dependency on quality and availability of medical imaging data, potential over-reliance on AI for diagnosis.	Improved accuracy and efficiency in disease diagnosis, potential for early detection of diseases.
Deep Learning [20]	Dermatology images	Deep learning for classifying skin cancer images, achieving performance on par with dermatologists.	Potential for overfitting, limited interpretability of deep learning models.	Improved accuracy in skin cancer diagnosis, potential for reducing dermatologist workload.
Deep Learning [21]	Retinal images	Deep learning for diabetic retinopathy diagnosis, achieving high sensitivity and specificity.	Dependency on quality and availability of retinal images, potential for algorithm bias.	Improved accuracy in diabetic retinopathy diagnosis, potential for early detection of the disease.
Deep Learning [4]	Chest X-ray images	Deep learning for diagnosing pneumonia from chest X-ray images, outperforming radiologists in certain cases.	Dependency on quality and availability of chest X-ray images, potential for algorithm bias.	Improved accuracy in pneumonia diagnosis, potential for reducing radiologist workload.
Machine Learning [5]	Activity recognition	Machine learning for recognizing activities in elderly patients, such as fall detection.	Dependency on accurate sensor data, potential for algorithm complexity.	Improved safety for elderly patients, potential for remote monitoring.
IoT [6]	Remote patient monitoring	IoT devices for remote monitoring of patients, enabling timely interventions and reduced hospital visits.	Dependency on reliable internet connectivity for data transmission, potential privacy concerns.	Potential for reducing healthcare costs, improved patient outcomes.
Machine Learning [7]	Electronic health records,	Machine learning for predicting patient outcomes, such as length of hospital stay or likelihood of readmission.	Dependency on quality and availability of electronic health records, potential bias in algorithm predictions.	Improved patient outcomes, potential for optimizing healthcare resource utilization.
IoT [8]	Various healthcare data	IoT devices for collecting diverse healthcare data, such as vital signs, environmental factors.	Interoperability challenges, data privacy concerns.	Potential for comprehensive healthcare monitoring, personalized treatment plans.
Machine Learning [10]	Various healthcare data	Machine learning for analyzing diverse healthcare data, extracting actionable insights for personalized treatment plans.	Data quality and availability, interpretability of machine learning models.	Potential for improving diagnostic accuracy, enhancing patient outcomes.

3. Dataset Used

The Comprehensive Disease Symptom and Patient Profile Dataset is a great way to find out more about how symptoms, demographics, and health factors are connected in a lot of different illnesses. This dataset gives a thorough look at symptoms like fever, cough, tiredness, and trouble breathing, as well as personal information like age and gender, and health markers like blood pressure and cholesterol levels. This information can be used by healthcare workers for clinical analysis and study. It can help them figure out how common and regular symptoms are in people with different medical conditions.

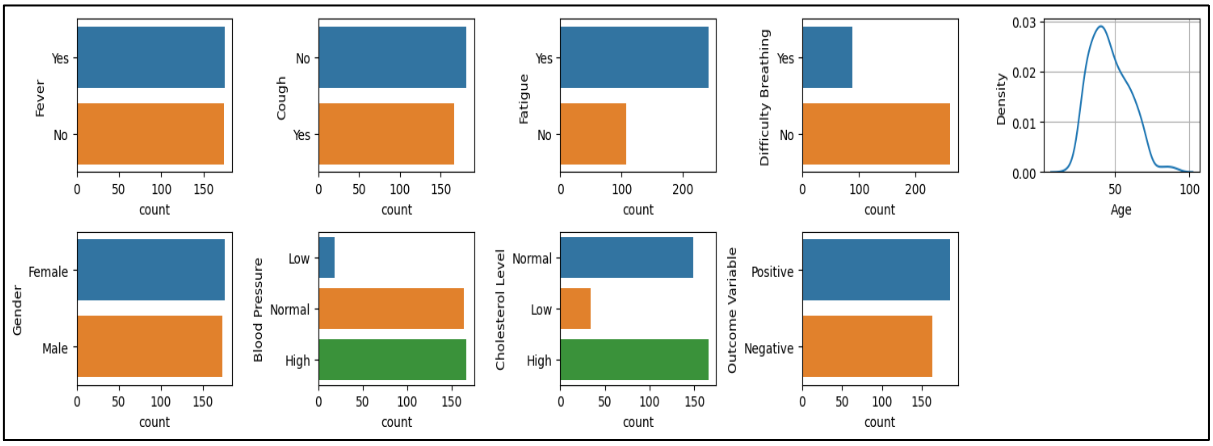

Fig 2: Visualize the dataset attribute with its count representation

Researchers can also use this information to look into the connections between symptoms and patient traits. This could lead to new ideas, ways to treat diseases, and ways to keep them from happening. This collection can be very helpful for healthcare tech businesses that want to train and test AI algorithms and prediction models. Companies can make more accurate and useful testing tools and healthcare apps by using this data. This will lead to better disease diagnosis and tracking based on signs and patient traits. Overall, the Comprehensive Disease Symptom and Patient Profile Dataset is a huge collection of data that can change the way we think about healthcare and help us get better at diagnosing, treating, and preventing diseases. This information could help people who study medicine, work in healthcare, or just like looking at data find secret trends and insights that can lead to new ideas in the healthcare field.

4. Machine Learning Methodology

Machine learning (ML) makes systems work better by using example data or past events to build models that get better over time. ML systems look at a lot of data to find trends and make mathematical models of how things behave. After that, these models are used to guess or decide what will happen. There are many tools that can be used to apply ML algorithms, which means that they can be used in many different fields and uses. Machine learning (ML) lets systems change and get better at what they do by constantly learning from data. This makes the results smarter and more efficient.

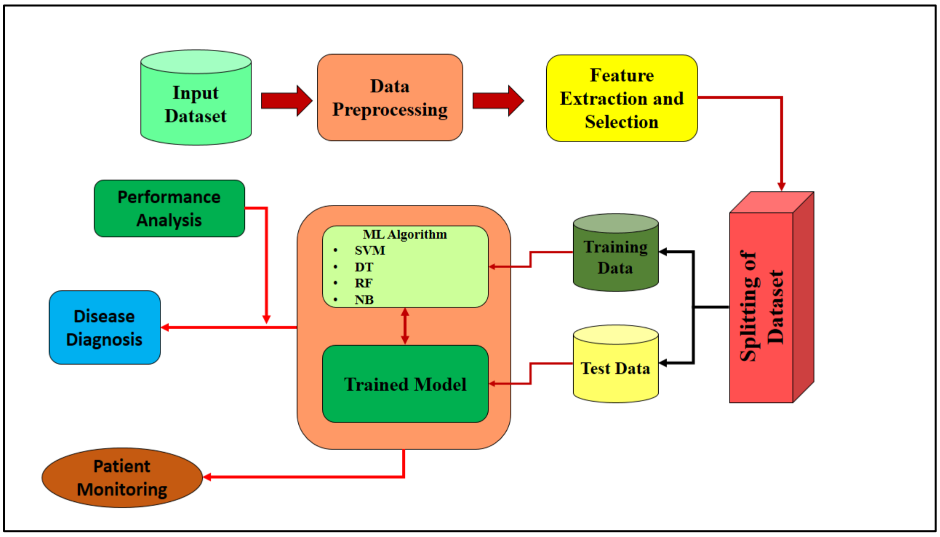

Fig 3: Proposed model architecture flow

A. Decision Tree

As part of machine learning, decision trees are a strong way to model actions based on case data or past events. If you want to make a system work better, you can use decision trees to make models that show how input variables (like symptoms, demographics, and health indicators) relate to output variables (like disease identification). choice trees divide the data into groups based on the values of input variables. They do this by making a tree-like structure, where each node inside the tree represents a choice based on an input variable and each node outside the tree represents the result. Looking at the decision tree's layout can help you understand the system's key parts and how they work together to make it work better. This can help people make better decisions and could even make the system work better.

Step 1: Split the dataset

- Let D be the dataset containing N samples with M features. Each sample i has features Xi = {xi1, xi2, ..., xiM} and an outcome variable yi indicating the diagnosis.

Step 2: Calculate impurity measure

- Calculate the impurity measure at the root node using a metric like Gini impurity or entropy.

$$I(D) = 1 - \sum_{\{k=1\}}^{\{K\}} pk^2$$

Where,

- K is the number of classes (2 in our case) and pk is the proportion of samples of class k in node D.

Step 3: Split the dataset

- Determine the best feature F and threshold T to split the dataset into two child nodes DL and DR. The splitting criterion can be based on information gain or another metric.

$$Information\ Gain = I(D) - \left(\frac{NL}{N} * I(DL) + \frac{NR}{N} * I(DR)\right)$$

Step 4: Repeat the splitting process

- Recursively apply steps 2 and 3 to each child node until a stopping criterion is met (e.g., maximum depth, minimum samples per leaf).

Step 5: Prediction

- Use the feature values to move through the decision tree from the root node to a leaf node for a new sample Xnew. Choose the class that has the most data in the leaf node as the expected result for Xnew.

B. Random Forest

The Random Forest algorithm is a strong group learning method used for sorting and predicting things. It works by building many decision trees during training and then showing the mode (for classification) or mean forecast (for regression) of each tree. The Random Forest method is shown below, step by step.

Step 1: Bootstrap Sampling

- To get a bootstrap sample, pick at random a part of the training data for each tree in the forest.

Step 2: Feature Selection

- In each node of the decision tree, pick at random a subset of the traits (mtry) that are present.

Step 3: Decision Trees

- Use the chosen features to make a decision tree from the bootstrap sample. At each node in the tree, split it using the feature that gives you the best split based on a measure like entropy or Gini impurity.

$$IG(p) = \sum_{i=1}^{T} Cpi2$$

$$IE(p) = -i = 1\sum Cpilog2(pi)$$

Step 4: Do Steps 1–3 again.

- To make a forest of choice trees, do steps 1 through 3 again and again.

Step 5: Prediction

- To classify something, each tree in the forest guesses what kind of thing it is. The final estimate is the tree with the most votes (mode).

$$IG(D,X) = I(D) - v \in X\sum \mid D \mid\mid Dv \mid I(Dv)$$

- When regression is used, each tree guesses what a new sample will be worth. The sum of all the tree forecasts is the end prediction.

$$Mode = argmaxci = 1\sum NI(yi = c)$$

C. Naïve Bayes

Naive Bayes is a simple machine learning method that works well and can be used to diagnose and track health problems. Naive Bayes can be used to figure out how likely it is that a patient has a certain disease based on their symptoms, personal information, and other health markers. Based on Bayes' theorem, the computer figures out how likely it is that a disease is the cause based on the symptoms and other data. Even though Naive Bayes is based on the "naive" idea that features are independent, it can work well in real life, especially with big datasets.

Naive Bayes can be used to look for trends that could point to health problems in data about patients that comes from smart tech, electronic health records, and other places. For detection, the program can help doctors figure out what diseases a person has by looking at their symptoms and other information about them. Naive Bayes is useful because it is easy to use, quick, and can handle data with a lot of dimensions. But it might not work well when features are strongly linked or when the idea of feature independence is broken. Overall, Naive Bayes can be a useful tool for diagnosing and keeping an eye on health problems. It can help with early spotting and personalized treatment plans.

- Calculate the prior probability of each class:

$$P(C_k) = Number\ of\ instances\ of\ class\ \frac{C_k}{Total\ number\ of\ instances}$$

For each feature X_i:

- Calculate the likelihood of each feature value x_i given each class C_k:

$$P(X\_i\ =\ x\_i \mid C\_k)\ =\ Number\ of\ instances\ of\ X\_i\ =\ x\_i\ in\ class\ C\_k\ /\ Number\ of\ instances\ in\ class\ C\_k$$

- Prediction:

For a new instance with features x_1, x_2, ..., x_n:

- Calculate the posterior probability of each class given the features using Bayes' theorem:

$$P(C\_k \mid x\_1, x\_2, \ldots, x\_n)\ \propto\ P(C\_k)\ \prod\_\{i = 1\}\hat{}\{n\}\ P(X\_i\ =\ x\_i \mid C\_k)$$

- Predict the class with the highest posterior probability:

$$\hat{}y\ =\ argmax\_k\ P(C\_k \mid x\_1, x\_2, \ldots, x\_n)$$

D. SVM

Support Vector Machines (SVMs) are strong machine learning models that can be used to track patients and sort diseases into groups. In a place with many dimensions, SVMs find the hyperplane that best separates groups of data points. SVMs can be used to put patients into different health groups based on their vital signs, symptoms, and other factors that are important for patient tracking. For illness classification, SVMs can use information about patients to guess how likely it is that a patient will have a certain disease. When the data can't be separated directly, SVMs work really well because they can use a kernel function to move the data into a higher-dimensional space where it can be separated.

1. Data Preparation:
   - Let X be the feature matrix with m samples and n features, and y be the corresponding vector of labels
2. Feature Scaling:
   - Standardize the features to have zero mean and unit variance to improve SVM performance
3. Model Training:
   - Choose a kernel function K (e.g., linear, polynomial, radial basis function)
   - Formulate the optimization problem to find the optimal hyperplane (decision boundary) that separates the data:

$$Minimize\,\frac{1}{2}\left||w|\right|^2 +\ C\ \sum_{i=1}\{m\}\xi$$

Subject to: $y\_i\ (w \cdot x\_i\ +\ b)\ \geq\ 1\ -\ \xi\_i$ $for\ i\ =\ 1, 2, \ldots, m, and\ \xi\_i\ \geq\ 0\ for\ i\ =\ 1, 2, \ldots, m.$

   - Solve the optimization problem to find w and b using methods like Sequential Minimal Optimization (SMO)
4. Model Prediction:

For a new sample x, predict its class label y using:

$$y\ =\ sign(w \cdot x\ +\ b)$$

5. Kernel Trick:

For non-linearly separable data, apply the kernel trick to map the data into a higher-dimensional space where it becomes linearly separable:

$$K(x_i, x_j) =\ \phi(x_i) \cdot \phi(x_j)$$

6. Hyperparameter Tuning:

Adjust hyperparameters like C (regularization parameter) and the choice of kernel function using techniques like cross-validation to improve model performance.

5. Result and Discussion

Table 2 shows the outcomes of four machine learning algorithms: Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), and Support Vector Machine (SVM). The accuracy, precision, recall, F1 Score, area under the curve (AUC), training time, and testing time were all changed. DT got an accuracy score of 87.63%, with memory scores of 85.22% and precision scores of 87.50%. The F1 number, which is the harmonic mean of accuracy and memory, is 86.45%, which means the result was fair. The Area Under the Curve (AUC) number of 88.86% means that the total result was good. DT needed 10.23 seconds to train and 2.25 seconds to pass. With a 93.65% success rate, RF did better than DT. It also got better at memory (92.42%) and accuracy (94.44%), which gave it an F1 score of 92.52%. With an AUC number of 96.54%, the result is very good. But training and testing took longer for RF (30.22 seconds) than for DT (5.45 seconds).

Table 2: Result of Machine learning algorithm with evaluation parameter

Method	Accuracy	Precision	Recall	F1 Score	AUC	Training Time (Sec)	Testing Time (Sec)
DT	87.63	87.50	85.22	86.45	88.86	10.23	2.25
RF	93.65	94.44	92.42	92.52	96.54	30.22	5.45
NB	82.45	84.74	80.74	87.41	84.85	1.33	1.02
SVM	91.75	90.14	89.88	90.87	93.25	50.14	10.41

NB got an accuracy score of 82.45%, with scores of 84.74% for precision and 80.74% for memory. With an F1 score of 87.41%, there is a good mix between accuracy and memory. With an AUC score of 84.85%, the result seems to be average. NB only needed 1.33 seconds for training and 1.02 seconds for tests. The Support Vector Machine (SVM) was able to get an accuracy of 91.75%, with recall values of 89.88% and precision values of 90.14%. The F1 score of 90.87% shows that the performance was fair. With an AUC score of 93.25%, the total result looks good. But among the algorithms, SVM took the longest to train (50.14 seconds) and test (10.41 seconds). In this case, RF was the best algorithm because it had the highest accuracy and AUC numbers. On the other hand, teaching and testing it took longer than with other algorithms. SVM also did well, but it took the longest to train and test. NB had the quickest training and testing times, but its accuracy and AUC values were lower than those of RF and SVM.

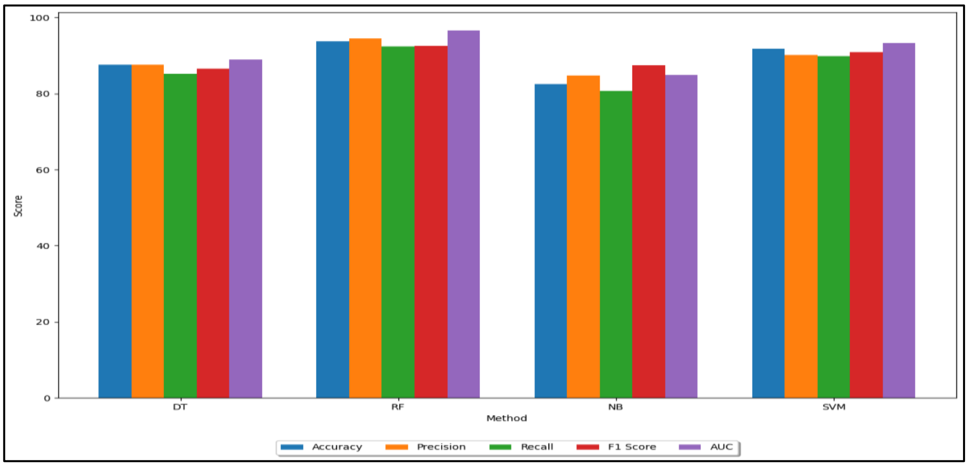

Fig 4: Performance Metrics for Different Machine Learning Methods

The training and testing loss of four machine learning models is shown in Table 3. These are Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), and Support Vector Machine (SVM). The mistake that happened during training is called "training loss," and the error that happened on data that wasn't seen during testing is called "testing loss." When DT was trained, it lost 0.215 and when it was tested, it lost 0.285.

Table 3: Training and Testing loss of ML Models

Algorithm	Training Loss	Testing Loss
DT	0.215	0.285
RF	0.123	0.198
NB	0.332	0.421
SVM	0.175	0.237

These numbers show that the model did pretty well during training, but it made a little more mistakes when it was tried on data it had not seen before.

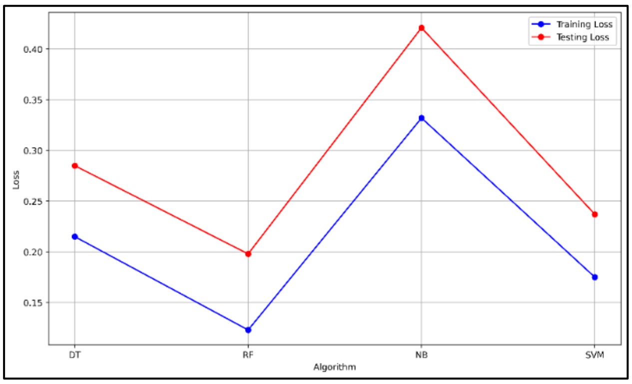

Fig 5: Training and Testing Loss of Machine Learning Algorithms

This difference in loss between training and tests may be a sign of overfitting to some degree. With lower training losses of 0.123 and testing losses of 0.198, RF did better than DT. The smaller difference between training and testing losses shows that RF generalizes better to new data, which means that it is a more stable model than DT.

When NB was trained, it lost 0.332 and when it was tested, it lost 0.421. Even though NB has a bigger training loss than DT and RF, its testing loss is closer to its training loss, which means it does a better job of generalizing. As a whole, though, NB has higher loss values than DT and RF.

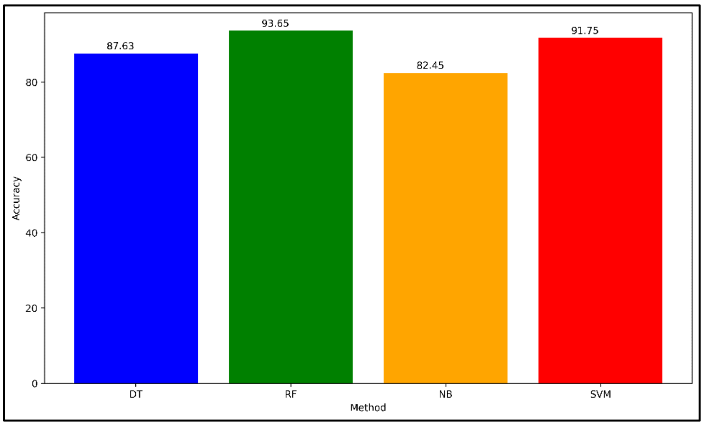

Fig 6: Accuracy Comparison of Model

When SVM was trained, it lost 0.175 and when it was tested, it lost 0.237. With such a small difference between the two loses, these numbers show that SVM did well both during training and testing. This suggests that it can generalize well. RF and SVM have smaller training and testing losses than DT and NB, which means they are better at reducing errors on both training and testing data. In particular, RF has the best mix between training and testing losses, which suggests that it can generalize well and be stable with data it hasn't seen before.

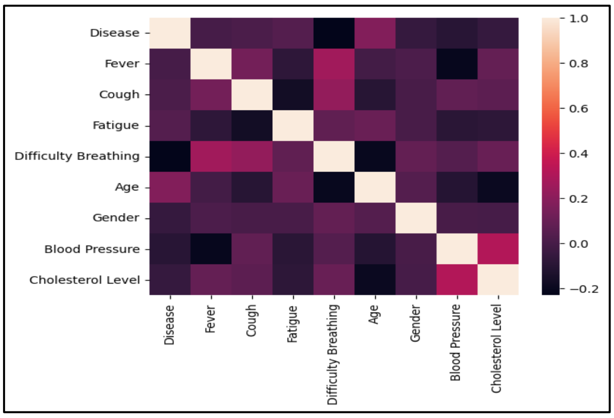

Fig 7: Representation of Training correlation for ML Model

6. Conclusion

A smart Internet of Things (IoT) system combined with machine learning algorithms has a lot of potential for personalized healthcare, especially when it comes to diagnosing and tracking patients in real time. When IoT devices are used to collect and send health data along with advanced machine learning algorithms, healthcare systems can provide care that is more efficient, accurate, and focused on the patient than ever before. This system lets healthcare workers keep an eye on their patients' health in real time, so they can catch any problems or health declines early. Computer programs that use machine learning can look at this information and find trends to predict possible health problems and make personalized treatment suggestions. This proactive method can help people get help when they need it, which can cut down on hospital readmissions and improve their general health. Also, adding machine learning to IoT healthcare systems makes it possible to create smart systems that help people make decisions. These tools can help healthcare workers make smart choices by giving them useful information from complicated health data. This makes healthcare service more efficient and also makes it easier for healthcare workers, so they can focus more on caring for patients. Overall, the smart IoT system for individual healthcare is a completely new way to provide healthcare. It could change the way healthcare is provided by making it more personalized, proactive, and patient-centered. As technology keeps getting better, more study and development in this area will be needed to fully utilize this system and make healthcare better for people all over the world.

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