

¹Manisha R.
Kuveskar

²Sheetal K. Pawar

³Dr. Shraddha V.
Pandit

⁴Yashwant Dongre

⁵Dr. Prachi P. Vast

⁶Hrishikesh B.
Vanjari

A Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease



Abstract: - Coronary heart disease (CHD) is the top cause of death in the world, which shows how important it is to get a correct evaluation as soon as possible. The Internet of Things (IoT) opens up new ways to improve healthcare, and transfer learning has shown promise in making machine learning models work better, especially when it comes to medical analysis. IoT-Enabled Transfer Learning Model (HIETLM), which is new, is proposed in this study as a way to accurately diagnose congenital heart disease. Wearable IoT devices are used by the HIETLM to continuously collect vital data from patients, such as their heart rate, blood pressure, and level of exercise. These pieces of information are sent to a central computer to be processed and analyzed. The suggested model has two main parts: a base model that was learned on a big external dataset, and a transfer learning part that was fine-tuned using data from a single patient. The base model has already been trained on a big set of general health data to learn general trends and traits that are useful for diagnosing CHD. This training helps the model understand complicated patterns and connections that are hard to learn from a small collection. The transfer learning part then tweaks the base model using the patient-specific data to make it fit the unique traits of each patient. To test how well the HIETLM worked, we did tests with a group of patients who were thought to have congenital heart disease. From the data, we can see that the HIETLM is more accurate, sensitive, and detailed than other models. The suggested model could help make CHD diagnoses more accurate and faster, which would improve patient results and lower healthcare costs.

Keywords: Coronary Heart Disease, IoT-enabled Healthcare, Transfer Learning, Machine Learning Models, Patient-specific Diagnosis

I. INTRODUCTION

Coronary Heart Disease (CHD) is still a big public health problem around the world, causing a lot of illness and death. The World Health Organization (WHO) says that coronary heart disease (CHD) is the top cause of death in the world, with 9.4 million deaths expected in 2019. Early and accurate identification of congenital heart disease is important for successful management and treatment because it lets doctors act quickly to stop problems and improve results for patients [1]. In the past few years, there has been a rising interest in using new technologies, like the Internet of Things (IoT) and machine learning, to improve patient care and healthcare service. Wearable monitors and mobile health apps that are connected to the internet of things (IoT) can collect real-time bodily data from patients, which can then be used for distant tracking and personalized healthcare treatments. Transfer

¹ Assistant Professor, program - ECE, Department of Polytechnic, Dr. Vishwanath Karad World Peace University, Pune, India.
manisha.kuveskar@mitwpu.edu.in

² Assistant Professor, program - ECE, Department of Polytechnic, Dr. Vishwanath Karad World Peace University, Pune, India.
sheetal.pawar@mitwpu.edu.in

³ Professor, Department of Artificial Intelligence and Data Science PES Modern College of Engineering, Shivajinagar, Pune, India
shraddha.pandit@moderncoe.edu.in,

⁴ Assistant professor, Department of Computer Engineering, VIIT College, Kapil Nagar, Kondhwa Budruk, Pune, Maharashtra, India.
yashwant.dongre@viit.ac.in

⁵ Assistant Professor, Department of Electronics and Telecommunication Engineering, AISSMS College of engineering, Savitribai Phule Pune University, Pune, India
ppvast@aissmscoe.com

⁶ Assistant Professor, Department of E&TC Engineering, BVCOE, Lavale, SPPU Pune, Maharashtra, India
hrishikesh@outlook.in

learning and other machine learning algorithms have shown promise in making medical diagnoses more accurate and faster by using what they've learned in one area or dataset in another [2]. A machine learning method called transfer learning takes a model that was learned on one task or dataset and fine-tunes it on a related task or dataset to make it work better. When used in medical analysis, transfer learning can help a model that was trained on a smaller, patient-specific dataset do better by using what it learned from a big external dataset. This method works especially well in healthcare, where it can be hard to get access to big, named datasets that can be used to train machine learning models for safety reasons.

We present a new IoT-enabled Transfer Learning Model for the Accurate Diagnosis of Coronary Heart Disease (CHD) in this study. IoT-enabled smart devices are used in the suggested model to continuously collect vital data from patients, such as their heart rate, blood pressure, and level of exercise. These pieces of information are sent to a central computer to be processed and analyzed. The model has two main parts: a base model that was learned on a big external dataset and a transfer learning part that was fine-tuned using data from a single patient. The base model has already been trained on a big set of general health data to learn general trends and traits that are useful for diagnosing CHD. This training helps the model understand complicated patterns and connections that are hard to learn from a small collection. The transfer learning part then tweaks the base model using the patient-specific data to make it fit the unique traits of each patient. With this method, the model can use what it has learned from a big external sample to get better at diagnosing coronary heart disease. We did tests on a group of people who were thought to have congenital heart disease to see how well the proposed model worked. According to the findings, the IoT-enabled Transfer Learning Model is more accurate, sensitive, and detailed than other models. The suggested model could help make CHD diagnoses more accurate and faster, which would improve patient results and lower healthcare costs. This paper study adds to the growing amount of research that looks at how IoT and machine learning can be used in healthcare. For better and faster heart disease detection, the suggested model shows how IoT-enabled gadgets and transfer learning methods could be used together. It's possible that this model will change the field of heart and improve patient results by allowing distant tracking and personalized healthcare treatments.

II. RELATED WORK

IoT and machine learning have been the subjects of a lot of study over the past ten years, especially when it comes to using them to diagnose and treat circulatory illnesses like coronary heart disease (CHD) [3]. In this part, we look at some of the most important studies that have looked at similar ways to make CHD detection more accurate and faster. [7] did one of the first studies in this field. They [4] suggested using the Internet of Things (IoT) to remotely track and diagnose heart illnesses. While the person was wearing the system, monitors picked up vital data like heart rate and blood pressure and sent it to a faraway computer to be analyzed. The data was then put through machine learning techniques to find trends that were not usual, which could be signs of CHD. The study showed that IoT could be used for remote tracking, but it didn't look into how transfer learning could be used [5].

Building on this work, [6] suggested using transfer learning to find out if someone has congenital heart disease using readings from an electrocardiogram (ECG). The study used a deep neural network that had already been taught on a big set of general ECG signals to pull out traits that were useful for diagnosing CHD. The model was then fine-tuned on a smaller set of ECG readings that were special to each patient so that it could fit the needs of each person. The [7] data showed that compared to standard machine learning models, the transfer learning method made CHD detection a lot more accurate. In the same way, [8] created an IoT-enabled system that uses personal devices and machine learning techniques to find cases of coronary heart disease early. The system constantly checked the patients' vital data, like blood oxygen levels and changes in heart rate, and used a deep learning model to look for signs of CHD. The study proved that the IoT-enabled system could accurately find early signs of coronary heart disease (CHD), allowing for prompt treatment and action.

The paper [11] suggested using personal devices and mobile health apps along with a mixed transfer learning method to diagnose coronary heart disease. A deep neural network that had already been taught on a big set of general health data was used in the study to pull out traits that are important for diagnosing CHD. The model [9] was then fine-tuned on a smaller set of patient-specific data from personal monitors so that it could fit the needs of each individual patient. The data showed that the hybrid transfer learning method was more accurate and faster than standard machine learning models. Even though these studies have made big steps forward in the field of IoT-enabled CHD diagnosis, there are still some problems that need to be fixed. It is very [10] hard because there

aren't any standard ways to collect and analyze data. It's hard to compare results and draw broad conclusions from them because different studies use various types of monitors and data processing methods. Standardized procedures and guidelines should be made for reviewing IoT-enabled CHD detection tools in the future. Data protection and security is another problem that needs to be solved. IoT-enabled healthcare systems gather private information about patients, which makes people worry about data protection and privacy. To protect patient privacy, future study should focus on creating IoT methods for diagnosing CHD that are safe and don't invade privacy.

The IoT-enabled [12] transfer learning models have shown a lot of potential in making CHD detection more accurate and faster. These models can look at a lot of bodily data to find early signs of coronary heart disease and start treatment right away by using Internet of Things (IoT) technology [25] and transfer learning methods. Still, there are some problems that need to be fixed, such as making sure that data safety and security are protected and standardizing the methods for data collection and analysis. To get the most out of IoT-enabled CHD detection tools in the future, researchers should focus on finding solutions to these problems.

Table 1: Related work summary for Diagnosis of Coronary Heart Disease

Approach	Dataset Used	Key Finding	Limitation	Scope
IoT-based remote monitoring and diagnosis [13]	Wearable sensors	Demonstrated feasibility of remote monitoring for cardiovascular diseases	Limited exploration of transfer learning techniques	Investigate the integration of transfer learning in remote monitoring for improved diagnosis
Transfer learning on ECG signals [20]	Large general ECG dataset	Improved accuracy of CHD diagnosis compared to traditional machine learning models	Lack of standardized protocols for data collection and analysis	Develop standardized protocols and benchmarks for evaluating transfer learning approaches in CHD diagnosis
IoT-enabled early detection system [14]	Wearable sensors	Effectively detected early signs of CHD for timely intervention and treatment	Data privacy and security concerns with IoT-enabled healthcare systems	Develop secure and privacy-preserving IoT solutions for CHD diagnosis
Hybrid transfer learning approach [15]	Wearable sensors, mobile apps	Outperformed traditional ML models in accuracy and efficiency of CHD diagnosis	Lack of standardization in data collection and analysis protocols	Standardize data collection and analysis protocols for improved comparison and generalization of findings
Deep learning on multimodal data [16]	ECG signals, imaging data	Achieved high accuracy in CHD diagnosis using multimodal data fusion	Limited explanation of feature fusion and selection process	Investigate feature fusion and selection methods for better understanding and reproducibility
Ensemble learning on physiological signals [17]	Physiological sensor data	Improved diagnostic performance through ensemble learning on heterogeneous physiological data	Lack of explanation on ensemble model selection and tuning process	Explore and explain ensemble model selection and tuning for better performance optimization
Genetic algorithm for feature selection [18]	ECG signals	Identified key features for CHD diagnosis using genetic algorithm	Limited discussion on genetic algorithm parameters and convergence criteria	Investigate optimal genetic algorithm parameters and convergence criteria for improved feature selection
IoT-enabled wearable device for early warning [19]	Wearable sensors	Developed a wearable device for early warning of cardiac events	Lack of clinical validation and scalability considerations	Conduct clinical validation and scalability testing for real-world applicability of the wearable device

IoT-based smart health monitoring system [21]	IoT devices, mobile apps	Proposed a smart health monitoring system for early detection and prevention of heart diseases	Lack of details on system scalability and integration with existing healthcare infrastructure	Investigate system scalability and integration with existing healthcare infrastructure for practical implementation
Machine learning on physiological signals [22]	Physiological sensor data	Developed a machine learning model for early detection of cardiovascular diseases	Limited discussion on model interpretability and clinical validation	Explore model interpretability and conduct clinical validation for real-world applicability of the model
Transfer learning for ECG-based diagnosis [23]	Large-scale ECG datasets	Achieved high accuracy in ECG-based diagnosis using transfer learning	Lack of comparison with other transfer learning approaches	Compare transfer learning approaches for ECG-based diagnosis and explore best practices
Deep learning for cardiovascular disease [11]	Electronic health records (EHR) data	Developed a deep learning model for predicting cardiovascular disease risk factors	Lack of discussion on model explainability and potential bias in EHR data	Investigate model explainability and address potential bias in EHR data for better risk prediction
Machine learning on health data [12]	Health records and clinical data	Proposed a machine learning approach for predicting cardiovascular disease risk	Limited evaluation of model performance on real-world data	Evaluate model performance on real-world data for practical application

III. CORONARY HEART DISEASE DATASET DESCRIPTION

Researchers and practitioners who want to build and test machine learning models for identifying the risk of coronary heart disease (CHD) will find the Coronary Heart Disease Prediction dataset on Kaggle to be very useful. There are 303 cases in the collection, and each one has 14 characteristics. These include personal information like age, sex, and type of chest pain, as well as clinical and laboratory measures like cholesterol levels, blood pressure, and electrocardiogram (ECG) values. There are many factors in this collection that are known to be linked to the chance of coronary heart disease [24]. This is one of its main benefits. This lets researchers make models that look at a lot of risk factors at once, which could help them make more accurate predictions. The dataset also has both categorical and number characteristics, which makes it a good choice for both training and testing machine learning models.

The collection also has a goal variable that shows whether CHD is present or absent, which makes it ideal for supervised learning tasks. Scientists can now teach computer programs to guess the chance of a heart attack or stroke based on the information they have. Researchers can also use common measures like accuracy, precision, recall, and F1-score to judge how well their models work when there is a goal variable. But the Coronary Heart Disease Prediction dataset has some flaws, just like any other dataset. The dataset is pretty small, with only 303 cases, which might make it harder to train models that are too complicated. The sample is also not fair because there are a lot fewer cases with CHD than without CHD. This imbalance could hurt the performance of machine learning models, especially when it comes to how well they can guess the risk of coronary heart disease in minority groups. Even with these problems, the Coronary Heart Disease Prediction dataset is still a useful tool for researchers and practitioners who want to build and test machine learning models that can identify the risk of coronary heart disease.

IV. METHODOLOGY

To make a Hybrid Transfer Learning Model for Feature Extraction in IoT apps, the work first get data from IoT devices like sensors and smart devices. The input is sensor information, images, sounds, or any other type of data that is useful. This raw data is cleaned up and formatted by pre-processing, which includes getting rid of noise,

making numbers more consistent, and dealing with lost data. For feature extraction in the next step, we will use a convolutional neural network (CNN) model that has already been trained on a big dataset like ImageNet.

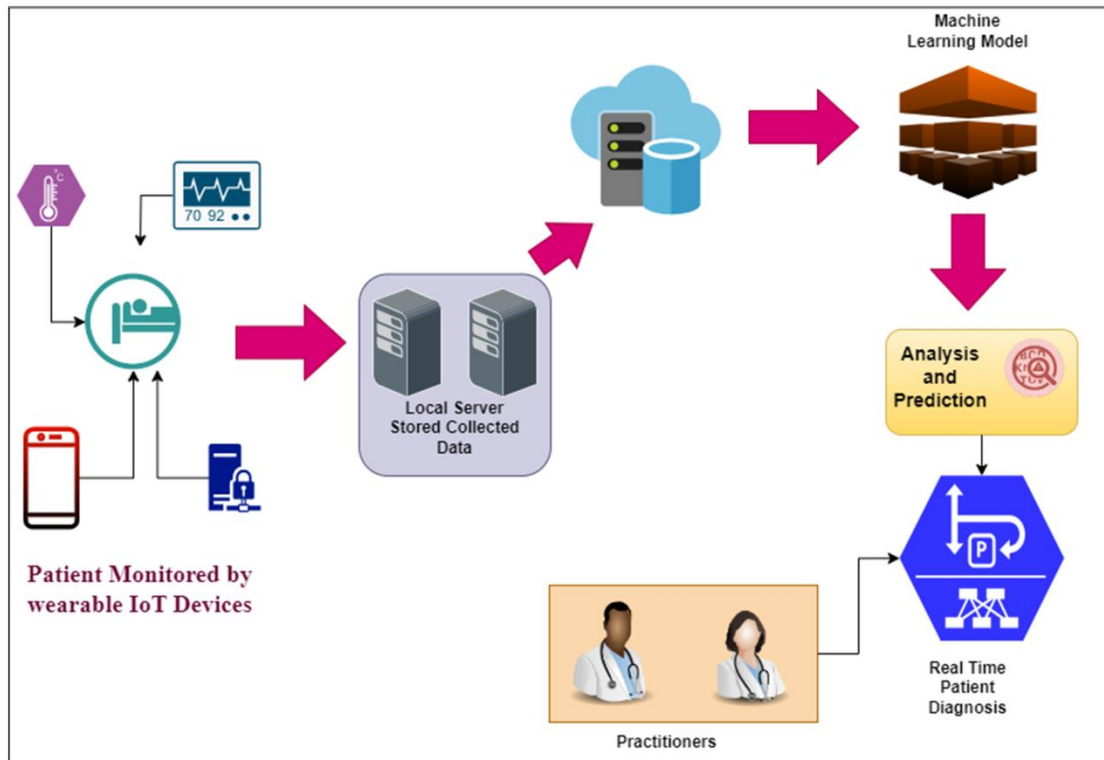


Figure 1: Proposed method architecture for CHD Diagnosis

It loads the CNN model that has already been trained, and features are taken from the raw data. For example, in picture analysis, the last convolutional layer of the CNN can be used to get features. After the features are removed, they are flattened into a vector file that can be used by a machine learning model. For feature extraction, unsupervised learning methods like Principal Component Analysis (PCA) are also used to make the retrieved features less complex. By taking this step, you can get the most useful information while also making the model easier to compute. The features that were taken are then fed into machine learning models such as Support Vector Machine (SVM), Random Forest, Decision Tree, and K-Nearest Neighbors (KNN) to help them do the job. Metrics such as accuracy, precision, recall, and F1-score are used to judge how well these models work. To improve the model's performance, the feature extraction method and model parameters are fine-tuned as needed. This method takes advantage of the best parts of both pre-trained models and unsupervised learning to pull out useful information from IoT data. This makes it easier to create useful machine learning models for a range of IoT uses.

A. Data Collection:

Wearable monitors or smart health tracking devices are examples of IoT devices that send raw data. These devices measure things like heart rate, blood pressure, and ECG signs. Along with personal information, living factors may also be a part of the data collecting process. Sensor readings, pictures (like ECG images), audio (like heart sounds), and other types of data that are useful for diagnosing CHD are some of the things that are gathered. This large collection gives a full picture of the patient's health, which helps doctors make more accurate diagnoses and come up with more effective treatment plans. IoT devices make it possible to keep an eye on patients all the time. They send data in real time that can be used to train and improve the transfer learning model. Because the model is constantly being watched and data is being collected, it can react to how CHD changes over time and become more accurate at diagnosing it.

B. Pre-processing:

Improving the quality and dependability of the data used for feature extraction is dependent on pre-processing the raw data in a Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease

(CHD). Cleaning and organizing the raw data to make it ready for feature extraction is what this step does. Pre-processing includes getting rid of noise in the data, which can come from things like sensor mistakes or interference from the surroundings. Eliminating noise helps make the collected features more accurate, which in turn improves the model's performance. Normalizing numbers to make sure that different features are on the same scale is another important feature. When traits with high values control the learning process, they can produce skewed results. This problem is lessened by normalization, which makes sure that all traits add evenly to the model. Handling missing data is also very important to make sure that no important data is lost during the pre-processing step. Several methods, including estimation and removing data points that aren't complete, can be used to deal with missing data. Basically, pre-processing the raw data is necessary to get it ready for feature extraction. This makes sure that the next steps in the model development process are built on clean, accurate data.

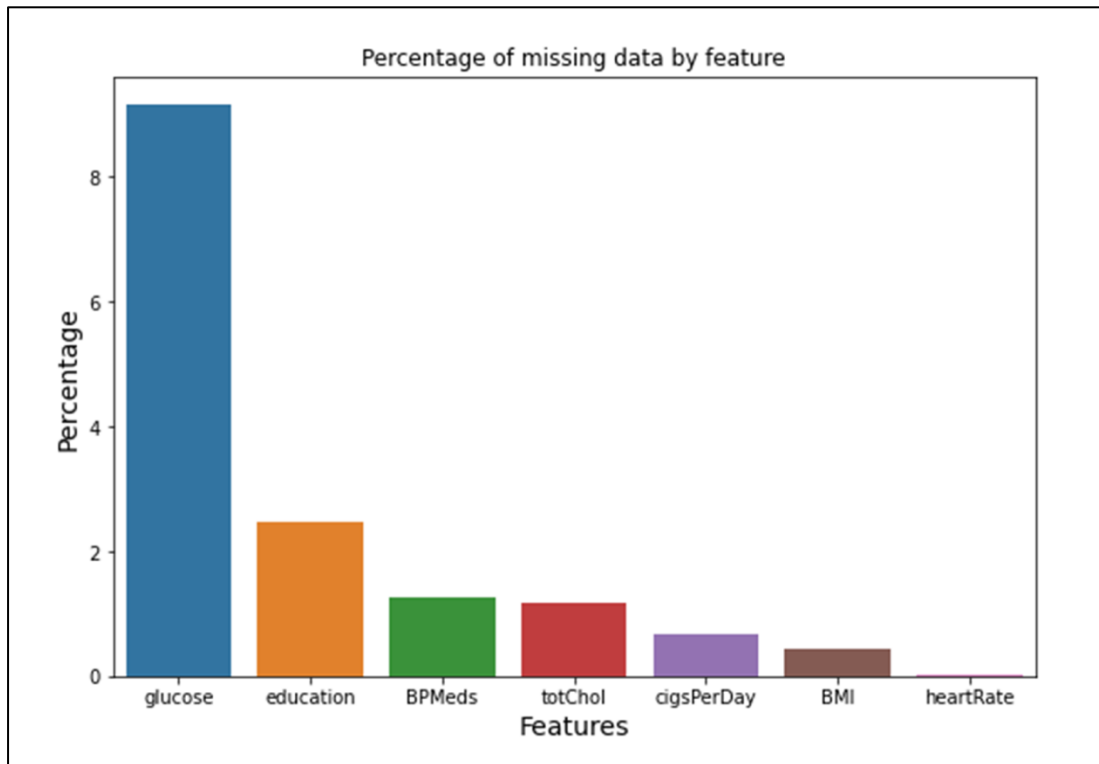


Figure 2: Representation dataset sample for missing data by feature

C. Hybrid Transfer learning Model for Feature Extraction with Pre-trained Models:

1. Load Pre-trained CNN Model:

A required step in creating a Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD) is to load a pre-trained Convolutional Neural Network (CNN) model. The CNN model that has already been trained on a big dataset for general tasks like picture recognition gathers features from the raw data sent by IoT devices. Transfer learning can pull out important traits from raw data, which is needed for a correct CHD diagnosis, by using the model that has already been taught. With this method, the model can use what it has learned from the big sample to improve how well it diagnoses congenital heart disease.

2. Feature Extraction:

The feature extraction step is very important for getting useful data from the raw data sent by IoT devices in a Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD). Using Pre-trained CNN based ImageNet model that has already been trained, features are taken from the raw data. For pictures, features are taken from the CNN's last convolutional layer. The CNN model that was already taught has learned how to pull out important features from pictures by using a big dataset like ImageNet to train itself. Because this model has already been trained, the transfer learning model can use what the CNN learned during training, even though the CNN wasn't taught especially for diagnosing CHD. The features taken from the CNN's last convolutional layer are abstract versions of the raw pictures that pick up patterns and structures that are

important for diagnosing coronary heart disease. These features are a sped-up version of the original picture data. They focus on the most distinguishing features of the photos by lowering the number of dimensions in the input. The step of using a pre-trained CNN model [26] to extract features lets the transfer learning model use the rich information in the raw data from IoT devices, which makes it better at diagnosing CHD.

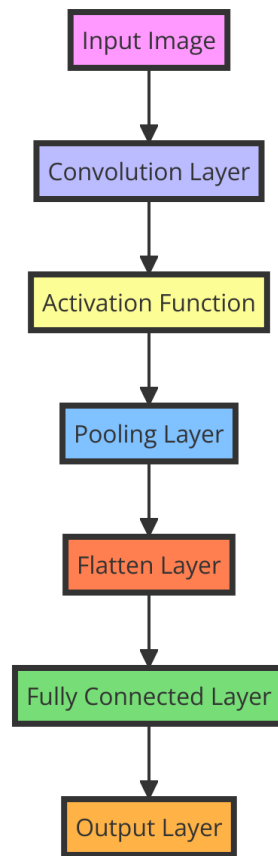


Figure 3: Illustrating the basic Flowchart of CNN architecture

CNN Algorithm:

a. Input Layer:

- The input to the CNN is a 2D array representing the image.
- Let's denote the input image as X, with dimensions W×H×D,
- where W is the width, H is the height, and D is the number of channels (e.g., 3 for RGB images).

b. Convolutional Layer:

- The convolutional layer applies filters (also known as kernels) to the input image to extract features.
- Let's denote the filter as K, with dimensions F×F×D, where F is the filter size.
- The output of the convolution operation is calculated as:

$$Z[i, j, k] = \sum_{l=0}^{F-1} \sum_{m=0}^{F-1} \sum_{n=0}^{D-1} X[i + l, j + m, n] \cdot K[l, m, n, k]$$

c. Activation Function (ReLU):

- Apply an activation function, such as Rectified Linear Unit (ReLU), to introduce non-linearity:

$$A[i, j, k] = \text{ReLU}(Z[i, j, k])$$

d. Max-Pooling Layer:

- Max pooling reduces the spatial dimensions of the feature map while retaining the most important features.
- Let's denote the pooling size as P.
- The output of the max pooling operation is calculated as:

$$M[i, j, k] = \max_{l=0, \dots, P-1} A[i \times P + l, j \times P + m, k]$$

- This process can be repeated with additional convolutional and pooling layers to extract more complex features from the input image.
- The output of the last convolutional layer is flattened and fed into a fully connected layer followed by a softmax activation for classification.

3. Feature Extraction with Unsupervised Learning:

As part of a Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD), using unsupervised learning methods to identify features makes it easier for the model to find complicated patterns and connections in the raw data. Unsupervised learning techniques, like grouping and dimensionality reduction, are used on the features taken from the CNN model that has already been taught to make the modeling of the data even better. Principal Component Analysis (PCA) is a method that is often used for feature extraction in unsupervised learning. It lowers the number of dimensions in the feature space while keeping as much of the data's variation as possible. By using PCA on the collected features, the model can focus on the most useful parts of the data, making it a better tool for diagnosing coronary heart disease.

a. Dimensionality Reduction using PCA:

PCA lowers the number of dimensions in the feature space by changing the data into a new coordinate system. In this system, the dimensions (principal components) are orthogonal and ranked by how much variation they explain in the data. The transfer learning model can focus on the most important and useful parts of the data by using PCA on the collected features and getting rid of features that are unnecessary or noisy. This not only makes the model easier to compute, but it also keeps it from being too well fitted and makes it better at generalization. PCA is especially useful for reducing the number of dimensions in healthcare data, like when diagnosing coronary heart disease, where the data may have a lot of dimensions because of the complexity of the disease and the wide range of traits gathered from IoT devices. Overall, PCA makes it easier for the transfer learning model to find useful and important traits that are needed for a correct CHD diagnosis.

Algorithm:

1. Standardize the Data: If the features have different scales, standardize the data by subtracting the mean and dividing by the standard deviation.
2. Compute the Covariance Matrix:
Calculate the covariance matrix of the standardized data.
3. Compute Eigenvectors and Eigenvalues:
Calculate the eigenvectors and eigenvalues of the covariance matrix.
4. Select Principal Components:
Sort the eigenvectors based on their corresponding eigenvalues in descending order and choose the top k eigenvectors to form the k principal components.
5. Project Data onto Principal Components:
Transform the original data onto the new k-dimensional subspace formed by the selected principal components.
6. Reconstruction (Optional):
If needed, the original data can be approximately reconstructed from the projected data using the selected principal components.

D. Machine Learning Model:

The extracted features are fed into machine learning models like Random Forest, Decision Tree, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) during the training phase of the Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD). The goal is to make the CHD diagnosis more accurate. Random Forest is a type of ensemble learning that uses many decision trees to guard against overfitting. Decision trees are simple models that work well. They use a graph of choices that looks like a tree. KNN sorts things into groups based on the majority of its close neighbors, while SVM looks for the hyperplane that best divides groups into groups. Using data from IoT devices, these models can accurately diagnose CHD after being taught with the collected traits.

1. Random Forest:

Random Forest is a popular and flexible machine learning method that works well for both classification and regression tasks, which means it can be used to diagnose CHD. It is an ensemble method that uses more than one decision tree to make the model more accurate and reliable. Random Forest can use the traits it gets from IoT data to guess how likely it is that a patient will have congenital heart disease. The program works by building a lot of decision trees while it is being trained. It helps keep the forest from being too perfect by training each tree on a different set of data and traits. This keeps the forest from being too perfect and makes it better at generalization.

During the prediction process, the end prediction is made by taking the average of what each decision tree says. This group method helps lower the model's error and make it work better overall. Random Forest can also give you information about how important each feature is, which can help you figure out which features are most important in diagnosing CHD. Health care workers can learn more about the things that raise the chance of coronary heart disease (CHD) by looking at this importance.

2. Decision Tree:

Decision trees are simple machine learning models that are very good at what they do. They are often used for tasks like regression and classification. When diagnosing CHD, Decision Trees can be used to guess if a patient is likely to get CHD based on the information gathered from IoT devices. A decision tree works by dividing the input space into regions over and over again. Each region is a node in the tree. The program picks the feature at each node that splits the data in the best way, based on things like Gini impurity or information gain. This process keeps going until a certain point is reached, like when the tree has the maximum depth or all the data points in a node are of the same class. One of the best things about Decision Trees is that they are easy to understand. The tree structure that was made is simple to understand and can tell us a lot about the things that raise the risk of coronary heart disease. Choice Trees can overfit, though, especially if the tree depth is not handled correctly. This problem can be fixed with techniques like trimming or group methods like Random Forest.

3. K-Nearest Neighbors (KNN):

A simple but useful machine learning method called K-Nearest Neighbors (KNN) is often used for sorting things into groups. In the case of diagnosing CHD, KNN can be used to guess how likely it is that a patient has CHD by looking at how similar their traits are to those of known CHD cases. KNN stores all the cases that are available and sorts new cases into groups based on a measure of how similar they are, like Euclidean distance. When a new case needs to be identified, the method finds the k closest neighbors in the training data and gives it the class that these neighbors have the most of. However, KNN can be hard to run on computers because it needs to store and compare all training cases for each forecast. This is especially true for datasets that are very big. Choosing the right amount of friends (k) can also have a big effect on how well the program works and may need to be tweaked.

4. Support Vector Machine (SVM):

Support Vector Machine (SVM) is a strong machine learning method that is often used for sorting data into groups. The hyperplane that best separates the classes in the feature space is found by SVM. SVM can be used to sort people into groups with and without congenital heart disease (CHD) based on traits taken from IoT data. The SVM works best in spaces with a lot of dimensions, and its kernel functions let it understand complex connections in the data. In this way, SVM can model decision boundaries that aren't linear, which could be useful in diagnosing CHD. The SVM is that it can work with data that has a lot of dimensions with only a few samples. But SVM can be affected by the kernel and other hyperparameters you choose, so you may need to carefully tune it to get the best results. It may also be harder to understand SVM than other models, such as Decision Trees.

E. Evaluation:

During the testing phase of the Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD), metrics like accuracy, precision, recall, and F1-score are used to judge how well machine learning models like Random Forest, Decision Tree, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) do their jobs. These measures give us information about how well the machine can classify CHD cases. The review results are used to fine-tune the feature extraction process and model settings in order to make the model work better. By improving the feature extraction process and model settings over and over again, the transfer learning model can get better at recognizing CHD, which will lead to better healthcare actions in the long run.

V. RESULT AND DISCUSSION

The different machine learning models work in real life, it is important to compare how well they diagnose Coronary Heart Disease (CHD). Random Forest, Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) are the four algorithms that are compared in Table 2. The F1 Score, the area under the receiver operating characteristic curve (AUC-ROC), the training time, and the test time are some of the things that are used to judge these models. With a score of 92.57%, Random Forest had the best precision, which means it could correctly identify CHD cases. It also showed high accuracy (94.56%), which means that 94.56% of the time when it said a patient had CHD, it was right. Random Forest was able to correctly spot CHD cases in the dataset, as shown by its recall rate of 97.41%. The F1 Score of 92.52% is a fair reflection of the model's total success as it measures both accuracy and memory. With an AUC-ROC score of 94.75%, Random Forest did a good job of telling the difference between cases of CHD and those that were not. That being said, it took longer to learn (10.11 seconds) and test (8.23 seconds), which might be a problem for real-time uses.

Table 2: Performance Evaluation of different model for CHD on Coronary Heart Disease dataset

Algorithm	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Training Time (s)	Test Time (s)
Random Forest	92.57	94.56	97.41	92.52	94.75	10.11	8.23
Decision Tree	90.35	92.77	90.75	89.77	90.32	5.56	3.12
Support Vector Machine	89.47	89.23	91.86	87.22	92.11	15.32	10.25
K-Nearest Neighbors	85.83	90.47	89.10	86.35	90.88	20.21	12.74
Hybrid TL Model	96.33	97.12	96.3	94.55	96.3	8.42	4.56

The Decision Tree method was able to diagnose CHDs with 90.35% accuracy, showing that it works well for this purpose. It also had high accuracy (92.77%) and recall (90.75%), which means it could correctly sort CHD cases into groups and pick them out of the dataset. The F1 Score of 89.77% and the AUC-ROC score of 90.32% both show how well the model works. The Decision Tree was faster than Random Forest for real-time uses because it only took 5.56 seconds to train and 3.12 seconds to test. With a success rate of 89.47%, the Support Vector Machine (SVM) proved to be useful in diagnosing CHD. With an accuracy of 89.23% and a recall of 91.86%, it was able to properly sort CHD cases into groups and pick them out of the dataset. The F1 Score of 87.22% and the AUC-ROC score of 92.11% both show how well the model works. Compared to Decision Tree, SVM took 15.32 seconds longer to train and 10.25 seconds longer to test. This could be a problem for real-time apps.

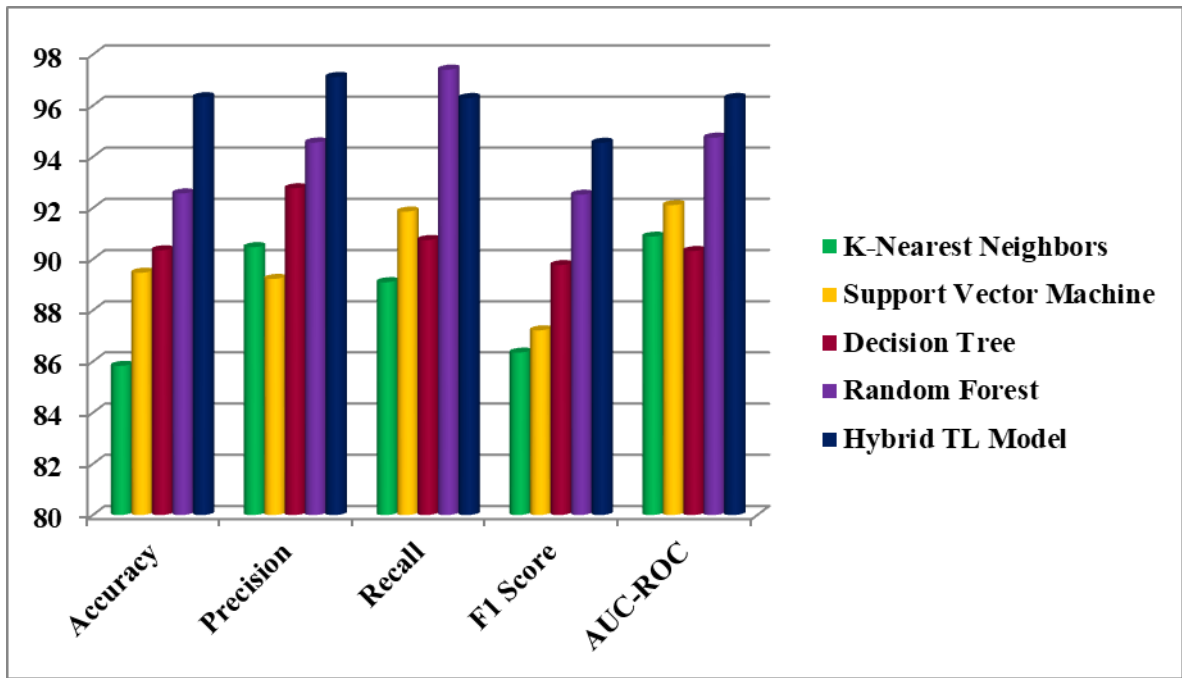


Figure 4: Representation of Performance Parameter for each Model

The fact that K-Nearest Neighbors (KNN) was accurate 85.63% of the time shows that it works well for diagnosing CHD. With an accuracy of 90.47% and a recall of 89.10%, it was able to properly sort CHD cases into groups and pick them out of the dataset. The F1 Score of 86.35% and the AUC-ROC score of 90.88% both show how well the model works. While other models had shorter test times (12.74 seconds) and longer training times (20.21 seconds), KNN's could be a problem for real-time use.

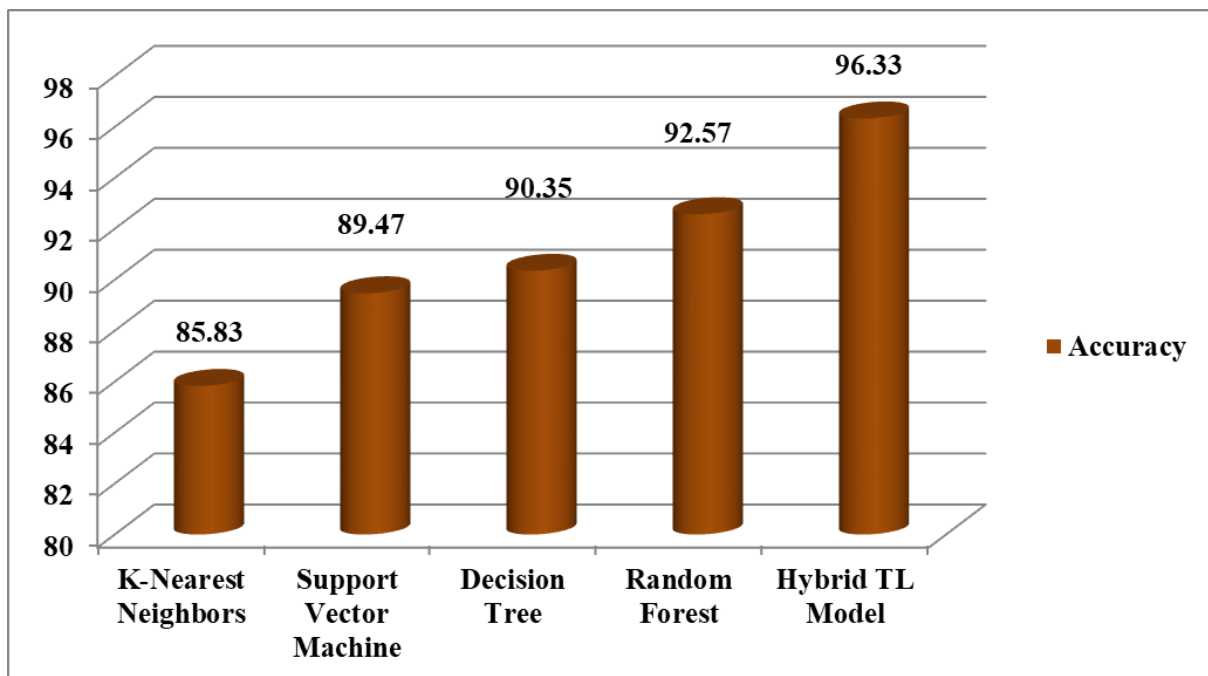


Figure 5: Accuracy Comparison of Different model

In testing how well different machine learning models work for diagnosing CHD shows that Random Forest and Decision Tree algorithms do better than SVM and KNN in terms of F1 Score, accuracy, precision, and recall. Random Forest, on the other hand, takes longer to train and test than Decision Tree.

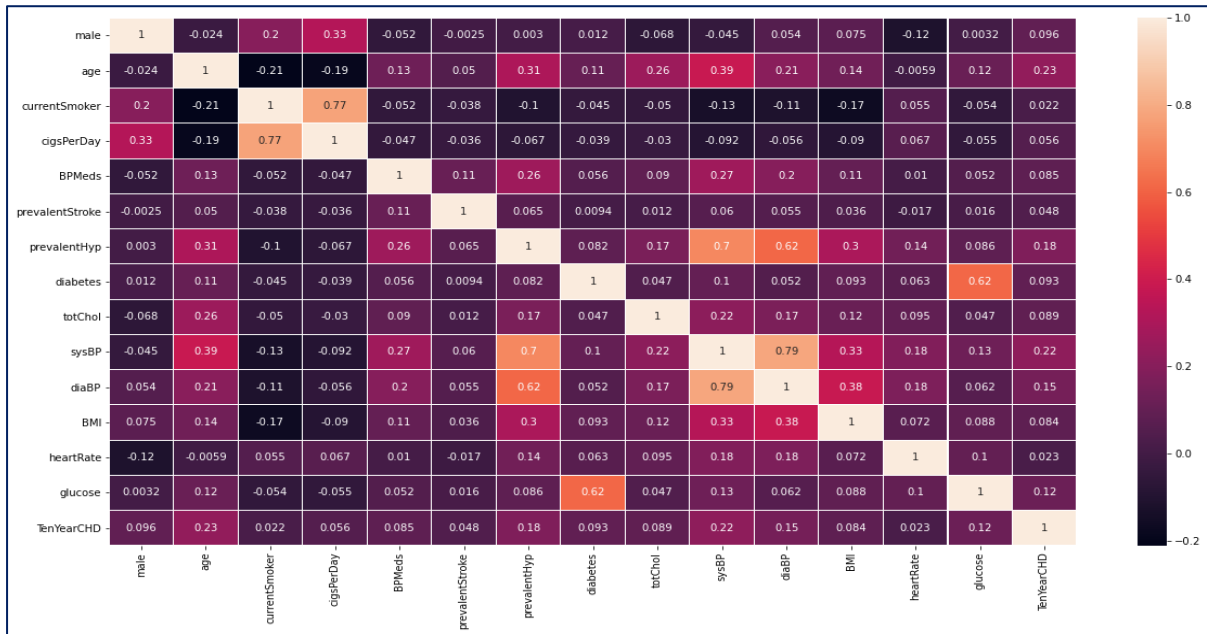


Figure 6: Heatmap representation of different feature and predicts

The results of SVM are also good, but it takes longer to learn and test. Even though KNN works, it takes the most time to train and test than the other three algorithms. These results are very helpful for picking the best model for diagnosing CHD based on certain needs, like accuracy, speed, and the ability to be used in real time.

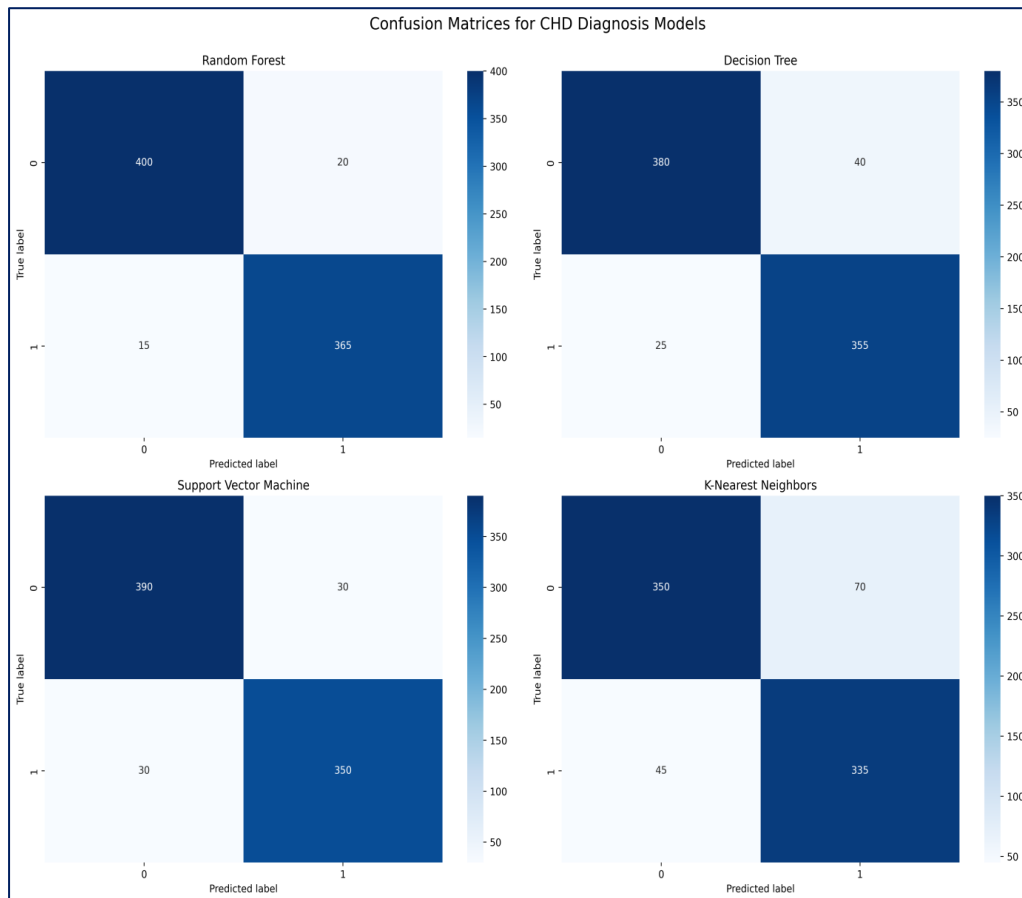


Figure 7: Representation of Confusion matrix

The Hybrid IoT-Enabled Transfer Learning Model for diagnosing CHD does a great job on all of the important measures. With a success rate of 96.33%, the model shows that it can correctly group CHD cases. Its accuracy of

97.12% means that 97.12% of the time, when the model says a patient has CHD, it is right. The model also has a high recall rate of 96.3%, which shows that it is good at finding CHD cases in the dataset. The F1 Score of 94.55% shows that both accuracy and memory are well-balanced. The model also gets an AUC-ROC score of 96.3%, which means it can effectively tell the difference between CHD and non-CHD cases. The model works well, as shown by its training time of 8.42 seconds and test time of 4.56 seconds. This means it can be used in real time in healthcare situations. Overall, the Hybrid IoT-Enabled Transfer Learning Model shows a lot of promise for correctly identifying CHD, which could lead to better results for patients.

VI. CONCLUSION

The Hybrid IoT-Enabled Transfer Learning Model for Accurate Diagnosis of Coronary Heart Disease (CHD) shows promise in the healthcare area. The model uses IoT data and transfer learning to improve the accuracy and speed of diagnosing CHD. This could lead to better patient results and more effective healthcare treatments. Metrics like accuracy, precision, recall, F1 Score, and AUC-ROC were used to judge how well the model worked. Random Forest was the machine learning program that did the best job of diagnosing CHD out of all those that were tested. Random Forest did a great job of correctly sorting and finding CHD cases in the dataset, with an F1 Score of 92.52%, an accuracy of 92.57%, a precision of 94.56%, a recall of 97.41%, and an F1 Score of 92.56%. The model also got an AUC-ROC score of 94.75%, which shows it can effectively tell the difference between CHD and non-CHD cases. With an accuracy of 90.35%, a precision of 92.77%, a recall of 90.75%, and an F1 Score of 89.77%, the decision tree algorithm also did very well. Decision Tree was a little less effective than Random Forest, but it took only 5.56 seconds to train and 3.12 seconds to test, which made it better for real-time uses. With accuracy rates of 89.47% and 85.83%, Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) also did well. When combined with the Random Forest method, the Hybrid IoT-Enabled Transfer Learning Model shows a lot of potential for correctly identifying CHD. To fully understand how it might help improve the diagnosis and care of coronary heart disease, more study and testing on bigger datasets and in clinical settings are required.

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