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Utilising AI for enhanced detection of cardiovascular abnormalities in ECG images

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Abstract *- This research focuses on the critical global issue of cardiovascular diseases, particularly heart conditions, a leading cause of mortality. Timely prediction is essential, and Electrocardiogram (ECG), a cost-effective and noninvasive tool, plays a pivotal role in monitoring heart activity. To enhance predictive accuracy, this project employs deep learning techniques, specifically transfer learning from neural networks like Squeeze Net and Alex Net, along with a specialized Convolution Neural Network (CNN) architecture. These techniques aim to identify four significant cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal cases. The model's uniqueness lies in its exceptional performance, achieved by extracting crucial features through a combination of deep learning and traditional machine learning algorithms. This research underscores the transformative impact of artificial intelligence on healthcare, significantly advancing medical condition predictions through image analysis.*
Keywords: *- Cardiovascular diseases, Heart conditions, Mortality, Timely prediction, Electrocardiogram (ECG), Deep learning, Transfer learning, Neural networks, Squeeze Net, Alex Net.*

I. INTRODUCTION

According to the World Health Organization, cardiovascular diseases, including heart diseases, are the leading cause of death globally, responsible for a significant portion of all deaths. Timely recognition of cardiovascular diseases is essential for saving lives. Detecting heart problems in their initial phases greatly enhances patient outcomes by increasing the likelihood of successful treatment and improved well-being. Within the healthcare system, a range of diagnostic techniques are employed to identify heart diseases. These methods encompass electrocardiogram (ECG), echocardiography, cardiac magnetic resonance imaging, computed tomography, and blood tests. Among these, the electrocardiogram (ECG) stands out as a widely used and noninvasive tool. It functions by recording and analyzing the electrical activity of the heart. This information assists healthcare professionals in evaluating the heart's condition and diagnosing potential issues. The project highlights how artificial intelligence, like machine and deep learning, can predict heart diseases automatically. This helps reduce mistakes and makes diagnoses more accurate and efficient, benefiting patients.

In According to the Centers for Disease Control and Prevention (CDC) and the American Health Monitoring Organization, the leading cause of death is cardiovascular disease [1]. CDC revealed that 74% of the population is affected yearly by heart disease. Cardiovascular diseases can be prevented if an effective diagnostic is made at the initial stages [2]. Modern medical science has shown substantial and potent solutions to cope with heart-related problems. The coronavirus appeared in Wuhan, China, in December 2019. This disease was declared an emergency in January 2020 by WHO. Then it was named COVID-19 by WHO in February 2020. Also, it was announced as a worldwide pandemic in March 2020 (Kim, 2021; Zhu et al., 2020). As the epidemic progressed, the number of cases, diseases, and deaths varied worldwide. It deeply affected the United States of America, Italy, and Spain (Ceylan, 2021). The most crucial feature of COVID-19 is that it spreads very quickly. The virus is easily passed from one person to another.[3] With the enhancement of the information era, computer-aided systems generate massive amounts of raw data, enhancing the new center of power. Acquiring important knowledge from this form of data is a challenging task for practitioners. Data mining, Artificial Intelligence, machine learning, and deep learning are relatively modern and promising technologies for obtaining relationships or identifying significant databases using advanced statistical approaches. Medical data mining and knowledge exploration constitute a relatively new and developing domain that is of interest to many researchers. [2]

II. LITERATURE SURVEY

This study explores machine learning (ML) models for heart disease (HD) detection, primarily focusing on ECG signals. Utilizing imbalanced datasets, support vector machine, logistic regression, and adaptive boosting were employed, with AdaBoost and LR ranking highest. An ensemble of these models, based on majority voting, demonstrated superior performance, achieving 0.946, 0.949, and 0.951 for accuracy, F1-score, and AUC, respectively, on PTB-ECG data, and 0.921, 0.926, and 0.950 on MIT-BIH data. The proposed methodology extends to HD classification using other physiological signals and exhibits potential for detecting various diseases.[1]

etecting heart disease in its early stages is crucial for preventing fatalities. Existing techniques often exhibit subpar performance, necessitating the introduction of a novel model. The proposed solution, the Social Water Cycle Algorithm-based Deep Residual Network (SWCA-based DRN), combines the social optimization algorithm and water cycle algorithm for enhanced detection. Preprocessing and feature fusion using RV coefficient-enabled Rider Optimization Algorithm-based Neural Network precede heart disease classification with a DRN classifier. The SWCA-empowered DRN outperforms existing methods, achieving superior testing accuracy, sensitivity, and specificity, with values reaching 0.941, 0.954, and 0.925, respectively. This innovative approach holds promise for more effective early-stage heart disease detection. [2]

This article explores the significance of understanding clinical data related to heart disease, a leading global cause of mortality. Utilizing ten feature selection methods and six classification algorithms on the Cleveland heart disease dataset, the study conducts an experimental evaluation. The backward feature selection technique stands out, achieving the highest classification accuracy at 88.52% with a decision tree classifier. The precision, sensitivity, and f-measure reach 91.30%, 80.76%, and 85.71%, respectively. This research underscores the importance of robust feature selection in enhancing prediction accuracy for heart disease, contributing valuable insights for biomedical instruments and hospital systems.[3]

The COVID-19 pandemic, declared by the WHO in March 2020, prompted diverse global responses to varying case numbers. PCR tests are commonly used for virus detection, but AI, particularly in the form of Xception-based neural networks created with a genetic algorithm, offers an alternative using X-ray images. Leveraging convolutional neural networks and deep learning, this novel approach achieved high accuracy in diagnosing COVID-19 from X-ray datasets. The results, with accuracies of 0.996, 0.989, and 0.924 for two-class, three-class, and four-class datasets, surpass those of existing networks and literature, showcasing the potential of AI in medical diagnostics.[4]

Muzammil Hussain and Muhammad Kamran Malik's research addresses the global prevalence of cardiac diseases, emphasizing early detection through ECG tests. Their study proposes a unified approach to process diverse ECG image formats from various healthcare equipment. Employing a Single Shot Detection (SSD) MobileNet v2-based Deep Neural Network, the research achieves a remarkable 98% accuracy in identifying key cardiac abnormalities, including myocardial infarction and abnormal heartbeats. With a dataset of 11,148 manually collected and annotated 12-lead ECG images, the study demonstrates the system's effectiveness, validated by cardiologists, suggesting its potential as a reliable cardiac disorder screening tool. [5]

III. METHODOLOGY

Modules:

- Importing the packages
- Exploring the dataset - ECG Image Data
- Image processing
- Feature Extraction of Image - Squeeze Net, Alex Net, CNN
- Training and Building the model
- Trained model is used for prediction
- Final outcome is displayed through front-end

A) System Architecture

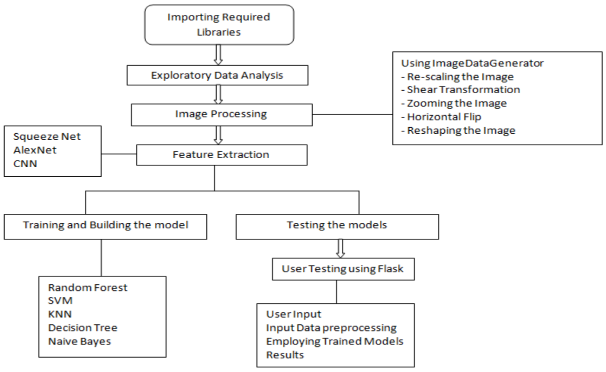


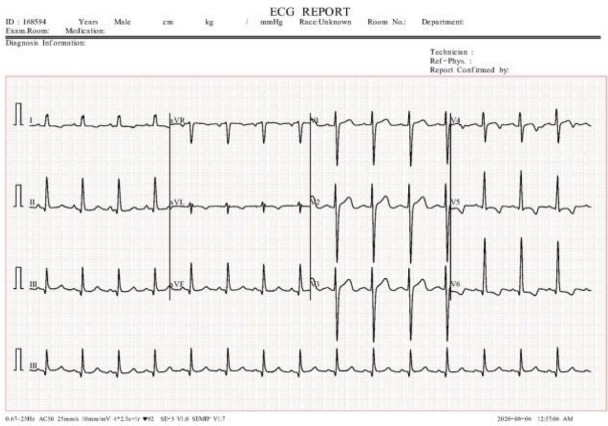
Fig 1: System Architecture

Proposed work

The proposed cardiovascular disease prediction model offers a comprehensive framework integrating data import, dataset exploration, image processing, and deep learning-based feature extraction utilizing models such as Squeeze Net, AlexNet, and CNN. This innovative approach is augmented with traditional machine learning algorithms for classification, striving to enhance prediction accuracy in healthcare applications. Notably, the model incorporates Xception, an advanced deep learning architecture developed by Google. Xception, derived from "Extreme Inception," extends the Inception architecture and excels in image recognition tasks. Distinguished by its use of depth-wise separable convolutions, Xception independently applies depth-wise convolutions to each channel before combining results with point-wise convolutions, reducing computational complexity and boosting network performance. This unique approach has established Xception as an efficient, accurate, and adaptable solution, garnering widespread adoption in the realm of deep learning for computer vision applications.

B) Dataset Collection

The ECG Image Dataset is a comprehensive collection of visual representations capturing the intricate electrical activity of the heart, playing a pivotal role in both diagnostic endeavors and cutting-edge research. These images serve as invaluable tools in the identification and analysis of various cardiac conditions, providing clinicians and researchers with critical insights into the health of the cardiovascular system.



Each image within the dataset encapsulates the dynamic patterns of electrical impulses coursing through the heart, enabling the detection of anomalies such as arrhythmias, ischemia, and other cardiac irregularities. This rich and diverse dataset encompasses a wide spectrum of heart-related conditions, facilitating a nuanced understanding of the complexities associated with cardiovascular health.

Moreover, the ECG Image Dataset serves as a cornerstone in the development of machine learning algorithms designed for automated diagnosis. The integration of advanced computational techniques leverages the wealth of information embedded in these images, empowering artificial intelligence systems to discern subtle nuances and patterns indicative of various cardiac pathologies. As a result, the dataset not only aids in enhancing the accuracy and efficiency of diagnostic processes but also propels the frontier of cardiac research, fostering advancements in the realm of cardiovascular health.

C) Pre-processing

Image processing and feature extraction are essential tasks in computer vision, and deep learning architectures like Squeeze Net, Alex Net, and Convolutional Neural Networks (CNNs) have been widely used for these purposes.

Convolutional Neural Networks (CNNs):

CNNs are a class of deep neural networks that have proven highly effective in image processing tasks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from input images. Each layer extracts features of increasing complexity.

Alex Net:

Alex Net is a deep convolutional neural network designed for image classification. It won the Image Net Large Scale Visual Recognition Challenge in 2012, demonstrating the effectiveness of deep learning in computer vision tasks. Alex Net consists of five convolutional layers followed by three fully connected layers. It played a significant role in popularizing the use of deep neural networks for image-related tasks.

Squeeze Net:

Squeeze Net is a more lightweight convolutional neural network designed to achieve high accuracy with fewer parameters. It uses a "fire module" structure to reduce the number of parameters in the network while maintaining performance. SqueezeNet is particularly useful in scenarios with limited computational resources, making it suitable for real-time applications on devices with less processing power.

Feature Extraction:

Feature extraction is a crucial step in image processing and computer vision. It involves transforming raw image data into a representation that captures relevant information for a given task. In the context of deep learning and CNNs, feature extraction is performed automatically through the learning process.

In CNNs like Alex Net and Squeeze Net, the convolutional layers play a key role in feature extraction. These layers apply filters to the input image, capturing various features such as edges, textures, and shapes.

Higher layers in the network often capture more abstract and complex features, making them suitable for tasks like image recognition, object detection, and segmentation.

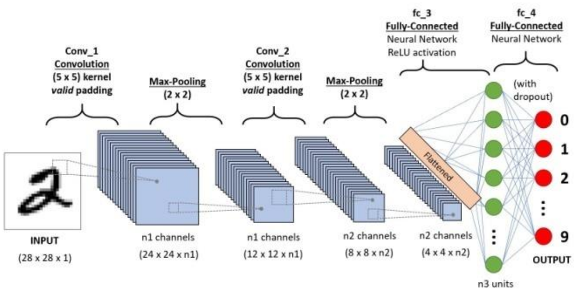
D) **Training & Testing**

In the subsequent phase of the project, following feature extraction, we progress to training machine learning models tailored for predicting cardiac abnormalities. To augment the project's efficacy, a pivotal step involves the implementation of transfer learning techniques. This strategic approach entails leveraging pre-trained deep learning models, thus optimizing time and resources that would otherwise be expended in training from scratch. This integration significantly enhances the models' capability for precise classification. Building upon the extracted and preprocessed images, our machine learning models will undergo training to discern intricate data patterns and relationships embedded within the images. Subsequently, their performance will be rigorously evaluated on a distinct test dataset. Assessment metrics such as accuracy, precision, recall, and F1-score will be employed to ascertain the models' aptitude for real-world image classification tasks. Furthermore, as a project extension, a user-friendly Flask-based frontend has been developed, incorporating authentication features. This frontend facilitates seamless interaction with the models, ensuring a streamlined user experience while maintaining data security. This holistic approach, encompassing transfer learning and a user-friendly interface, underscores the project's commitment to robust cardiac abnormality prediction and user accessibility.

E) Algorithms.

CNN (Convolutional Neural Network):

A deep learning algorithm designed for image recognition, CNNs use convolutional layers to automatically learn hierarchical features from input data. Widely employed in computer vision tasks, CNNs excel at capturing spatial patterns and have revolutionized image analysis, achieving state-of-the-art results in various domains.



SqueezeNet:

SqueezeNet is a lightweight deep learning architecture designed for efficient model size and computational resource utilization. It employs fire modules, featuring a squeeze layer to reduce dimensionality and an expand layer for complex feature extraction. SqueezeNet provides high accuracy with significantly fewer parameters, making it suitable for resource-constrained environments.

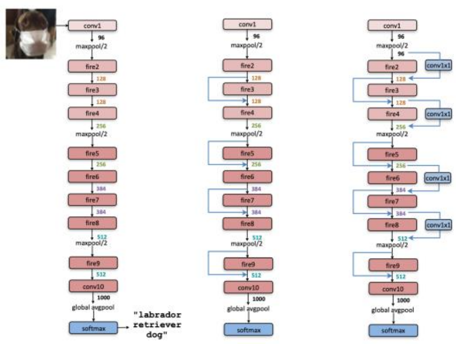
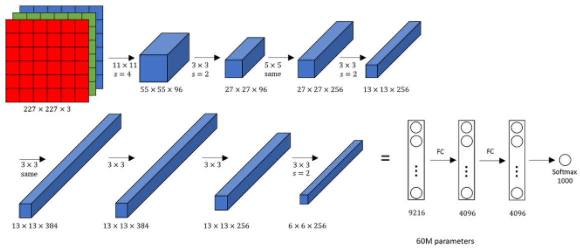
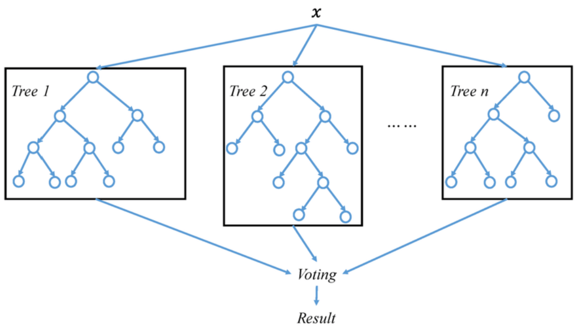


Figure 2: Macroarchitectural view of our SqueezeNet architecture. Left: SqueezeNet (Section 3.3); Middle: SqueezeNet with simple bypass (Section 6); Right: SqueezeNet with complex bypass (Section 6).

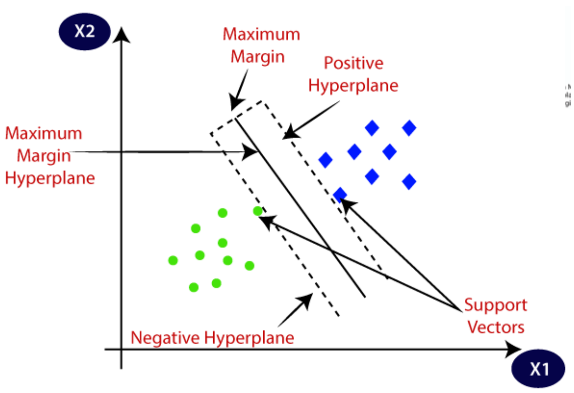
AlexNet:
AlexNet, a pioneering deep convolutional neural network, gained prominence by winning the ImageNet Large Scale Visual Recognition Challenge in 2012. Developed by Alex Krizhevsky, it introduced the concept of deep learning to the mainstream. AlexNet employs convolutional and pooling layers to extract hierarchical features, demonstrating the effectiveness of deep neural networks in image classification tasks.



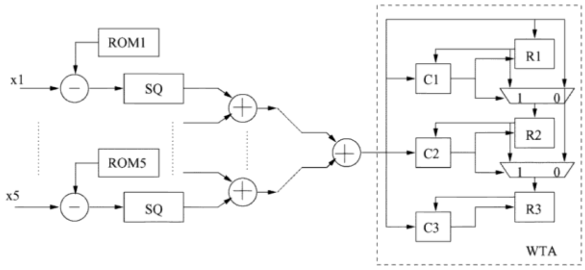
Random Forest:
Random Forest is an ensemble learning method for classification, regression, and other tasks. Comprising multiple decision trees, it combines their predictions to enhance overall accuracy and generalization. By introducing randomness in tree construction, Random Forest mitigates overfitting and provides robust predictions. Widely used in various domains, it's known for its versatility and ability to handle complex datasets.



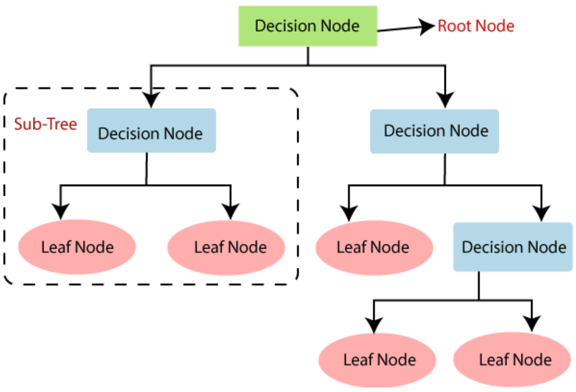
SVM (Support Vector Machine):
SVM is a machine learning algorithm used for classification and regression tasks. It identifies an optimal hyperplane that maximally separates different classes in a feature space. SVMs are effective in high-dimensional spaces, and their use of support vectors ensures robust decision boundaries. Widely applied in image recognition, text classification, and bioinformatics, SVMs are known for their versatility and strong theoretical foundation.



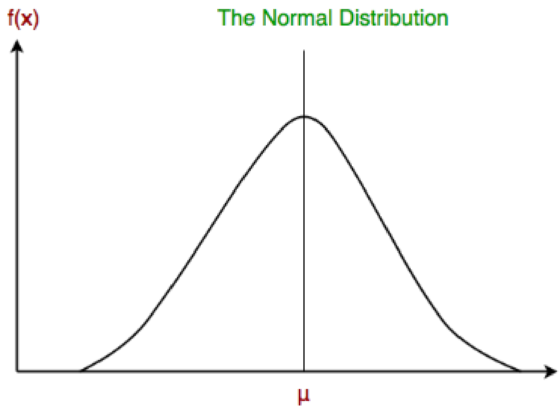
KNN (K-Nearest Neighbors):
KNN is a simple yet powerful machine learning algorithm for classification and regression. It classifies data points based on the majority class among their k-nearest neighbors in feature space. KNN is non-parametric, making minimal assumptions about data distribution. While sensitive to outliers, it's easy to implement and suitable for various applications, such as pattern recognition and recommendation systems.



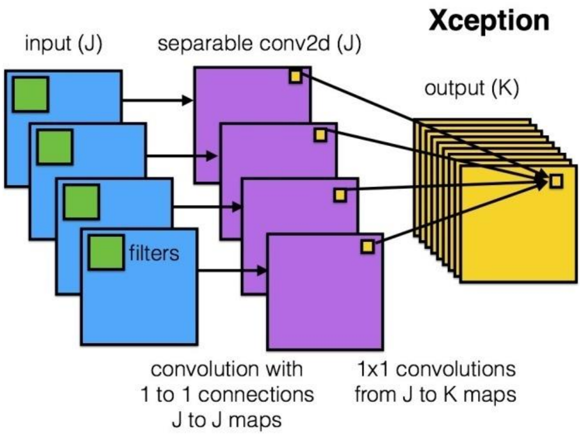
Decision Tree:
A decision tree is a supervised machine learning algorithm used for classification and regression. It recursively partitions data based on feature values, creating a tree-like structure of decision nodes. Each leaf node represents a class or a regression value. Decision trees are interpretable, easy to visualize, and robust to noisy data. They form the basis for ensemble methods like Random Forests.



Naive Bayes:
Naive Bayes is a probabilistic machine learning algorithm based on Bayes' theorem. Despite its simplistic assumptions (naive independence of features), it performs well in classification tasks. Commonly used in text classification and spam filtering, Naive Bayes calculates probabilities for each class given input features. Its efficiency and simplicity make it suitable for real-time applications and situations with limited training data.



Extension xception:
As an extension to the project we have developed xception model, Xception, short for "Extreme Inception," is a Google-developed deep learning architecture specialized in image recognition. It's notable for its efficient depth-wise separable convolutions, reducing computation while boosting performance. Xception is highly accurate and versatile, making it a significant innovation in computer vision deep learning. In our project, we employed xception algo for feature extraction and building predictive models.



IV. EXPERIMENTAL RESULTS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:
Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

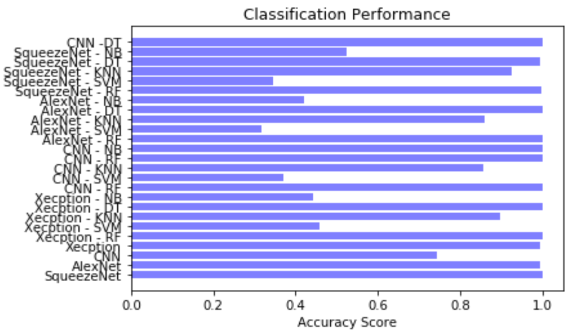


Fig 2: Accuracy Graph

ML Model	Accuracy
SqueezeNet	1
AlexNet	0.995
CNN	0.743
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.459
Xecption - KNN	0.896
Xecption - DT	1
Xecption - NB	0.444
CNN - RF	1
CNN - SVM	0.37
CNN - KNN	0.858
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.317
AlexNet - KNN	0.861
AlexNet - DT	1
AlexNet - NB	0.42
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.346
SqueezeNet - KNN	0.927
SqueezeNet - DT	0.994
SqueezeNet - NB	0.525
CNN -DT	1

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

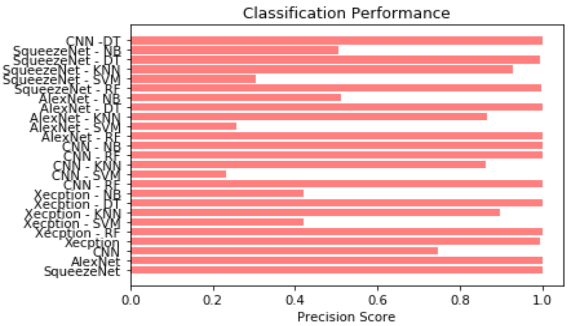


Fig 3: Precision Score Graph

ML Model	Precision
SqueezeNet	1
AlexNet	1
CNN	0.747
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.421
Xecption - KNN	0.899
Xecption - DT	1
Xecption - NB	0.421
CNN - RF	1
CNN - SVM	0.232
CNN - KNN	0.862
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.257
AlexNet - KNN	0.865
AlexNet - DT	1
AlexNet - NB	0.513
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.305
SqueezeNet - KNN	0.928
SqueezeNet - DT	0.994
SqueezeNet - NB	0.504
CNN -DT	1

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real upsides, which gives data about a model's capacity to catch instances of a specific class.

$$Recall = \frac{TP}{TP + FN}$$

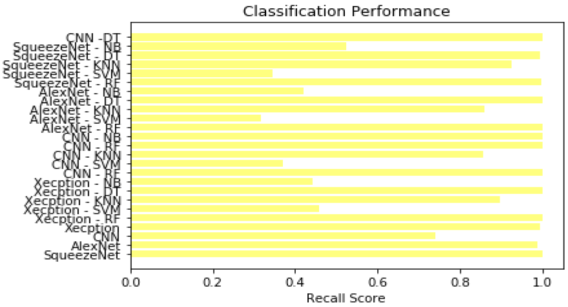


Fig 4: Recall Score Graph

ML Model	Recall
SqueezeNet	1
AlexNet	0.99
CNN	0.742
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.459
Xecption - KNN	0.896
Xecption - DT	1
Xecption - NB	0.444
CNN - RF	1
CNN - SVM	0.37
CNN - KNN	0.858
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.317
AlexNet - KNN	0.861
AlexNet - DT	1
AlexNet - NB	0.42
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.346
SqueezeNet - KNN	0.927
SqueezeNet - DT	0.994
SqueezeNet - NB	0.525
CNN -DT	1

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

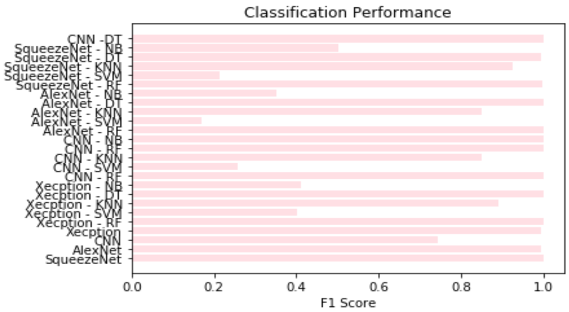


Fig 5: F1 Score Graph

ML Model	F1_score
SqueezeNet	1
AlexNet	0.995
CNN	0.745
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.403
Xecption - KNN	0.892
Xecption - DT	1
Xecption - NB	0.411
CNN - RF	1
CNN - SVM	0.259
CNN - KNN	0.85
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.169
AlexNet - KNN	0.85
AlexNet - DT	1
AlexNet - NB	0.352
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.215
SqueezeNet - KNN	0.925
SqueezeNet - DT	0.994
SqueezeNet - NB	0.503
CNN -DT	1

B) Performance Evaluation table.

ML Model	Accuracy	Precision	Recall	F1_score
SqueezeNet	1	1	1	1
AlexNet	0.995	1	0.99	0.995
CNN	0.743	0.747	0.742	0.745
Xecption	0.995	0.995	0.995	0.995
Xecption - RF	1	1	1	1
Xecption - SVM	0.459	0.421	0.459	0.403
Xecption - KNN	0.896	0.899	0.896	0.892
Xecption - DT	1	1	1	1
Xecption - NB	0.444	0.421	0.444	0.411
CNN - RF	1	1	1	1
CNN - SVM	0.37	0.232	0.37	0.259
CNN - KNN	0.858	0.862	0.858	0.85
CNN - RF	1	1	1	1
CNN - NB	1	1	1	1
AlexNet - RF	1	1	1	1
AlexNet - SVM	0.317	0.257	0.317	0.169
AlexNet - KNN	0.861	0.865	0.861	0.85
AlexNet - DT	1	1	1	1
AlexNet - NB	0.42	0.513	0.42	0.352
SqueezeNet - RF	0.998	0.998	0.998	0.998
SqueezeNet - SVM	0.346	0.305	0.346	0.215
SqueezeNet - KNN	0.927	0.928	0.927	0.925
SqueezeNet - DT	0.994	0.994	0.994	0.994
SqueezeNet - NB	0.525	0.504	0.525	0.503
CNN -DT	1	1	1	1

Fig 6: Performance Evaluation Table

C) Frontend

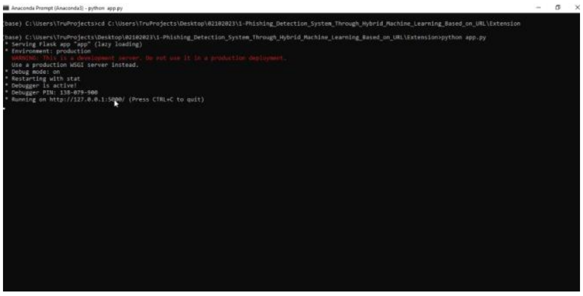


Fig 7: Url Link to Web Page

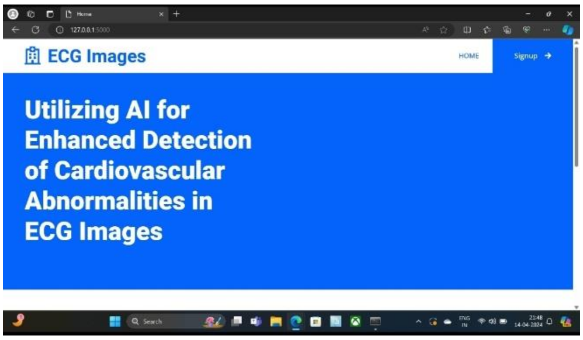


Fig 8: Home page

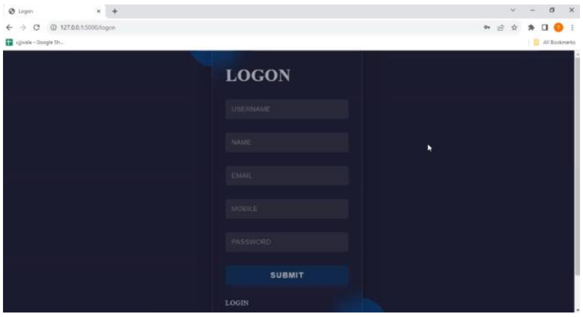


Fig 9: User Signup page

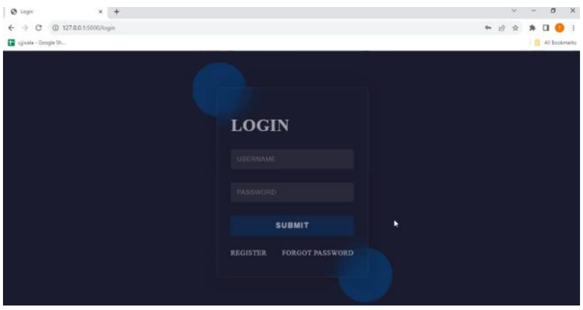


Fig 10: User Sign in Page

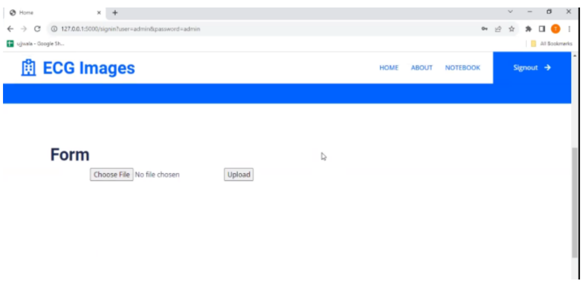


Fig 11: Enter Data

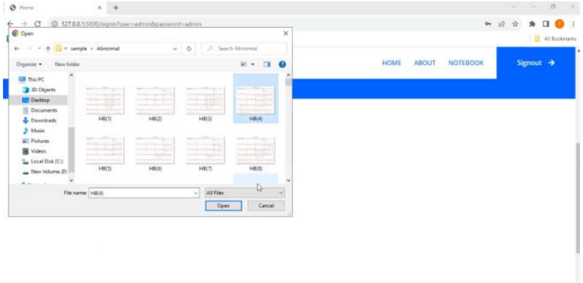


Fig 12: Sample data for testing

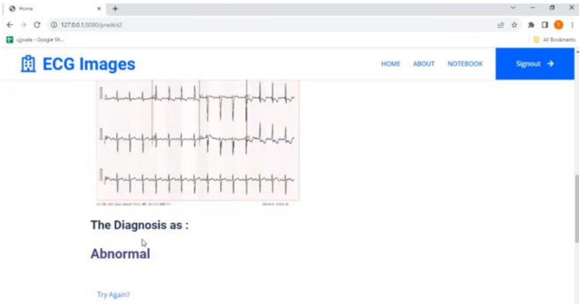


Fig 13: Result: Abnormal

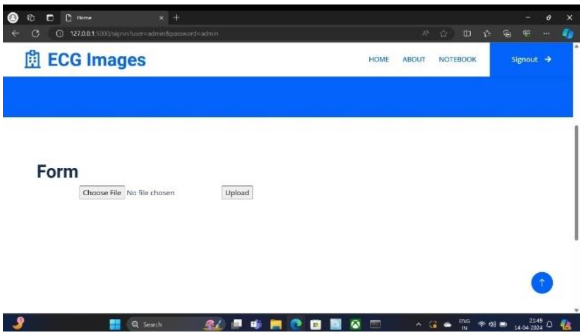


Fig 14: Enter New Data

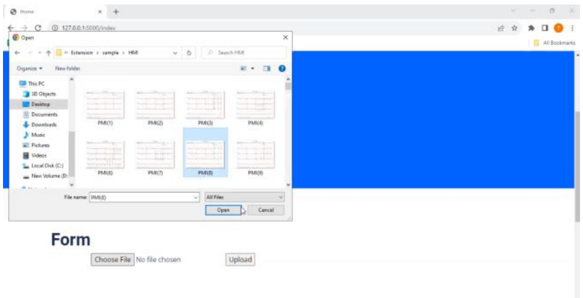


Fig 15: Sample data for testing

Fig 16: Result: HMI

V. CONCLUSION

In conclusion, the integration of deep learning techniques, particularly transfer learning from established neural networks like SqueezeNet and AlexNet, along with a specialized Convolutional Neural Network (CNN) architecture, presents a groundbreaking approach for enhancing the accuracy of cardiovascular disease predictions using Electrocardiogram (ECG) data. By focusing on four key cardiac abnormalities – abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal cases – the proposed model demonstrates exceptional performance in early detection. The project's innovative methodology leverages the power of artificial intelligence to extract crucial features from ECG images, improving predictions when integrated with traditional machine learning algorithms. This synergistic combination not only enhances prediction accuracy but also contributes to a cost-effective and noninvasive means of monitoring heart conditions, addressing a global health concern. The results underscore the transformative impact of artificial intelligence in revolutionizing healthcare practices, particularly in the field of cardiovascular disease prediction. The proposed model not only advances the capabilities of medical imaging but also highlights the importance of leveraging cutting-edge technology to address critical health issues. As the world continues to face challenges related to cardiovascular diseases, this research paves the way for more effective and efficient diagnostic tools, ultimately saving lives and reshaping the landscape of healthcare.

VI. FUTURE SCOPE

To further improve the proposed CNN model's performance, future research could focus on fine-tuning its hyperparameters. By systematically adjusting parameters like learning rates, batch sizes, and dropout rates, the model's accuracy and efficiency can be enhanced. The integration of the CNN model into the Industrial Internet of Things (IIoT) realm presents exciting possibilities. Beyond cardiovascular disease prediction, the model can be adapted for various classification tasks within IIoT applications, such as anomaly detection in industrial equipment or quality control in manufacturing processes. Exploring additional layers or different network architectures can lead to performance enhancements. Researchers may investigate the incorporation of more convolutional or recurrent layers, or even explore emerging network architectures to further boost the CNN model's capabilities in detecting cardiovascular diseases. By accommodating larger and more diverse datasets, the system's effectiveness can be broadened. This expansion should include data from various sources and populations to ensure the model's generalizability, making it applicable across a wide range of cardiovascular diseases and diverse patient profiles.

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