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DETECTION OF CARDIOVASCULAR DISEASES IN ECG IMAGES USING MACHINE LEARNING AND DEEP LEARNING METHODS

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Abstract: Early prediction is urgent since cardiovascular disorders, especially heart issues, are a main source of mortality around the world. By following heart movement, the harmless, minimal expense Electrocardiogram (ECG) aids the conclusion of different circumstances. Four significant cardiovascular irregularities are recognized utilizing deep learning procedures: unusual heartbeat, myocardial localized necrosis, history of myocardial dead tissue, and typical occasions. This further develops expectation accuracy. The task mixes a redid CNN design with move gaining from deep neural networks like SqueezeNet and AlexNet. By separating critical attributes, this strategy might be utilized with customary ML methods to improve forecasts. The proposed model is one of a kind in that it performs particularly well, enormously working on the capacity to conjecture clinical issues from photographs. It stresses how significant computerized reasoning is to changing medical services techniques. Utilizing ECG pictures, the incorporated Xception model further develops include extraction for the distinguishing proof of heart irregularities. ML models utilize removed qualities as information

sources, which works on the calculations' ability to recognize complex examples and irregularities. The incorporation of refined include extraction strategies with versatile ML calculations upgrades the venture's ability to convey exact clinical diagnostics. The framework's reasonableness is featured by the worked on client cooperations made conceivable by Cup with SQLite. It gives safe information exchange, signin, and viable testing for better medical services strategies.

Index terms - Cardiovascular, deep learning, electrocar diogram (ECG) images, feature extraction, machine learning, transfer learning.

1. INTRODUCTION

The World Health Organization reports that heart disease, or cardio-vascular disorders, is the primary driver of mortality internationally. An expected 17.9 million lives are lost to them every year, making around 32% of all fatalities internationally. Myocardial areas of localized necrosis (MI), generally alluded to as cardiovascular disease, represent more than 85% of all heart disease-related fatalities [1]. Assuming cardiovascular disease is

really analyzed and treated almost immediately, many lives can be saved [1]. The medical services framework utilizes various strategies, including blood tests, processed tomography, cardiovascular attractive reverberation imaging, electrocardiograms (ECGs), echocardiograms (echo), and registered tomography, to recognize heart issues [2], [3]. The ECG is a generally utilized, sensibly valued, and harmless technique for deciding the heart's electrical action [4]. It is utilized to identify cardiovascular problems related with the heart [4], [5]. From the ECG waves, a highly trained doctor can recognize heart disease. In any case, this manual strategy requires a ton of exertion and could create mistaken discoveries [5].

Computerized reasoning progressions in medical care can possibly altogether bring down clinical errors. In particular, the robotized forecast of cardiovascular sicknesses through the utilization of deep learning and ML techniques [3], [6]-[10]. To separate and pick the right highlights prior to continuing on toward the characterization step, ML methods need a specialist substance. By anticipating or changing over the information into a new, lower-layered highlight space while keeping the relevant data from the info information, include extraction is the most common way of limiting how much elements in an informational collection [11], [12].

Include extraction is to consolidate unique elements into a lower-layered space to make another arrangement of highlights (which are unmistakable from the information includes) that separate the vast majority of the data from the information. One of the most involved procedures for removing highlights is head part examination. [13, 14]. Highlight choice, then again, is the most common way of disposing of

pointless and superfluous elements (aspects) from the informational index to prepare ML calculations. Different procedures are accessible for highlight choice; they can be sorted as either supervised or unsupervised, contingent upon regardless of whether the result name is expected for include determination. There are three ways to deal with supervised feature determination: the channel procedure, the covering technique, and the implanting strategy. [11, 12].

Cardiovascular diseases have been anticipated utilizing an assortment of ML strategies. Utilizing the UCI Cleveland heart disease dataset, Soni et al. [15] inspected various ML procedures, including decision trees (DT), neural networks (NN), K-nearest neighbors (K-NN), and Naïve Bayes (NB). They came to the conclusion that, at 89%, DT had the best accuracy. Utilizing the UCI Cleveland heart disease dataset, Dissanayake and Md Johar [16] examined the effect of the component determination technique on ML classifiers for heart disease prediction.

2. LITERATURE SURVEY

Cardio-vascular diseases (CVDs) are normal in the populace and can be deadly. As indicated by information from a new survey, smoking, hypertension, corpulence, and cholesterol are contributing variables to a rising demise rate. As a result of the previously mentioned factors, the illness' seriousness is deteriorating. We actually must research these boundaries' progressions and what they mean for CVD. This requires the use of contemporary techniques to identify the disease early and add to a decrease in the passing rate. [3] The fields of man-made reasoning and information mining give huge exploration amazing open doors

because of their high level procedures that guide in the forecast of CVD cases and assist with tracking down designs in their way of behaving from immense measures of information. These figures' results will uphold doctors' independent direction and early conclusion, bringing down the likelihood that a patient would pass on. [6, 8, 24, 28] The different arrangement, information mining, ML, and deep learning models that are utilized to anticipate cardiovascular and vascular problems are thought about and revealed in this work. The overview is separated into three areas: deep Learning Models for CVD expectation, ML Models for CVD, and Order and Information Digging Methods for CVD. This overview additionally aggregates and reports the presentation estimates used to report precision, the dataset used for characterization and expectation, and the apparatuses utilized for every class of these methodologies.

The P-QRS-T wave that addresses the heart's cardiovascular action is called an electrocardiogram, or ECG. The patient's sickness is shown by the little varieties in the repolarization and depolarization examples of the electric potential. The analysis of heart wellbeing can utilize these clinical time space parts of the ECG waveform. Accurately distinguishing the ECG classes with the natural eye is very difficult on account of clamor and moment morphological boundary values. [5] This study surveys various computer-aided cardiac diagnostic (CACD) frameworks, insightful methods, impediments confronted, and the eventual fate of cardiovascular infection screening. The natural separating qualities can't be sufficiently addressed by methods like the wavelet change that were intended for time area, recurrence change space, and time-

recurrence space examination. [6, 9, 10, 23] Subsequently, this paper goes into additional profundity into nonlinear strategies that might get on unpretentious changes in the ECG sign and deal better exactness when there is commotion present. By utilizing these nonlinear properties, a CACD framework can help clinical experts in making more exact determinations of cardiovascular disease.

In contrast with different sicknesses around the world, heart disease (HD) is a lethal disease that kills the best number of people. Numerous significant lives can be saved assuming the affliction is recognized early and precisely. Clinical testing, heart sounds, electrocardiogram (ECG) signals, computed tomography (CT) pictures, and different techniques can all uncover the presence of HD. Among every one of the techniques, the ID of HD from ECG information is fundamental. The ECG tests of the members were viewed in this article as fundamental contributions for the HD location calculation. Numerous supportive distributions on the arrangement of HD utilizing different ML and DL models have been distributed as of late. It has been noticed that the recognition precision is diminished with uneven HD information. To further develop HD identification, proper DL and ML models have been tracked down in this work, and the fundamental characterization models have been made and assessed [6]. The objective of the Generative Adversarial Network (GAN) model is to deal with uneven information by making and using extra misleading information for identification. Furthermore, this exploration fosters a group model utilizing long short-term memory (LSTM) and GAN that performs better compared to the singular DL model utilized in this paper [9]. The proposed GAN-LSTM model

beats different models as far as exactness, F1-score, and area under the curve (AUC), with upsides of 0.992, 0.987, and 0.984, individually, as indicated by the recreation results utilizing the standard MIT-BIH. Like this, the GAN-LSTM model performs better compared to any remaining models on the PTB-ECG dataset, with accuracy, F1-score, and AUC upsides of 0.994, 0.993, and 0.995, separately. Among the five models inspected, it is shown that the GAN model plays out the best, while the NB model has the most minimal location possibility. Extra review might be finished by choosing and using an assortment of elective outfit models and datasets, with equivalent outcomes for execution investigation. Different ailments and medical care issues can likewise be dealt with utilizing the proposed best discovery strategies.

The electrocardiogram (ECG) and the doctors who decipher it currently have godlike indicative abilities on account of artificial intelligence (AI) [3]. AI changes over the ECG, a typical harmless heart test that is coordinated into training work processes, into a screening device and indicator of cardiovascular and non-heart sicknesses, habitually in asymptomatic people. This is made conceivable by simulated intelligence's capacity to track down often subclinical examples in enormous datasets without the requirement for hard-coded rules. The numerical starting point for regulated artificial intelligence calculations is made sense of in this survey [7], which likewise covers a couple of explicit man-made intelligence ECG cardiovascular screening calculations. These incorporate calculations for distinguishing underlying and valvular illnesses, wordy atrial fibrillation from a following taken during ordinary sinus beat, and left ventricular

brokenness. As well as presenting issues for information security, the ability to gain from enormous informational indexes without the need to grasp the organic system has made it conceivable to analyze sicknesses other than coronary episodes, such as Coronavirus. [6, 10]The computer based intelligence ECG must be entirely analyzed and approved in real clinical settings, very much like some other clinical trial. At last, the utilization of AI might give immense versatility to democratize medical care, with portable structure factors that empower the social occasion of clinical grade ECGs through cell phones and wearables.

While assessing cardiovascular arrhythmias in clinical practice, an electrocardiogram (ECG) is an essential symptomatic device. This study [8] utilizes a deep learning engineering that was recently prepared on an expansive picture informational collection to naturally analyze ECG arrhythmias in patients by sorting their ECGs into the fitting cardiovascular states. The last grouping is performed by taking care of the recovered highlights into an essential back spread brain organization, which is input into an exceptionally deep convolutional neural network (AlexNet). To survey the proposed system, three unmistakable ECG waveform conditions are browsed the MIT-BIH arrhythmia information base [23]. This review's essential objective is to apply a deep learning approach that is direct, reliable, and basically versatile for ordering the three particular heart infections that were picked. The got discoveries showed that exceptionally elite presentation rates may be accomplished by flowing a norm back proliferation brain network with a moved deep learning highlight extractor. The most noteworthy precise acknowledgment rate recorded was 98.51%,

with a testing accuracy of around 92%. These discoveries exhibited that adaptable deep learning, which saves the difficulty of preparing a deep convolutional neural network all along, is a successful mechanized technique for recognizing cardiovascular arrhythmias [21, 25, 26].

3. METHODOLOGY

i) Proposed Work:

Image processing and model development are the two fundamental phases of the proposed model. To set up the information for picture handling, we use ImageDataGenerator for tasks including rescaling, shear change, zooming, flipping, and reshaping. During the model development stage, highlights are removed utilizing profound learning models, for example, Crush Net, CNN, and AlexNet [20, 22]. Conventional machine learning techniques including Random Forest, SVM, KNN, Decision Tree, and Naive Bayes are then used to evaluate the extracted features. By foreseeing cardiovascular sickness with high exactness and trustworthiness, this widely inclusive system desires to make a significant commitment to medical services applications. To recognize heart anomalies from ECG pictures, the coordinated Xception model further develops include extraction [23]. ML models utilize extricated qualities as data sources, which works on the calculations' ability to recognize complex examples and anomalies. The combination of refined highlight extraction methods with strong ML calculations upgrades the task's ability to convey exact clinical diagnostics. The framework's common sense is featured by the improved on client communications made conceivable by Carafe with SQLite. It gives

safe information exchange, signin, and successful testing for better medical services techniques.

ii) System Architecture:

- Patient ECG pictures act as the info information for the methodology, what begins at stage 23. These photographs act as the expectation framework's beginning stage.
- The information is exposed to deeplearning models during the element extraction stage. These models, which can naturally perceive relevant examples and highlights inside the ECG pictures, incorporate SqueezeNet, AlexNet, CNN [30, 31, 33], and a lengthy xception model.
- After attributes are removed from the ECG pictures, ML order calculations use them as info. Subsequent to handling the recovered attributes, the ML models group or foresee things utilizing what they have realized during preparing.
- The ML arrangement results showing the presence or nonappearance of specific cardiovascular oddities are displayed in the last result.

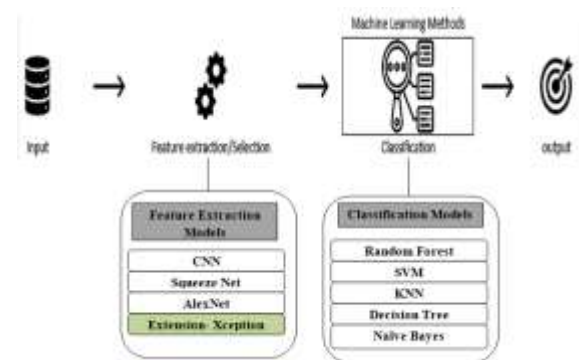


Fig 1 System Architecture

iii) Dataset collection:

Imagining the heart's electrical action with ECG Image Data [23] supports the distinguishing proof of cardiovascular issues and powers ML based computerized diagnostics. Visual portrayals of heart electrical movement are found in ECG image data, which is helpful for study and conclusion. These photos assume a basic part in the discovery of heart issues and are used in ML to give mechanized determination. In this way, these are TYPE Pictures.



Fig 2 ECG Image Data

iv) Image Processing:

- Across a few basic levels, image processing is vital for independent driving frameworks' object identification procedure. The initial step is to improve the info picture for additional investigation and change by transforming it into a mass article. The classes of things to be found are then indicated, characterizing the specific gatherings that the calculation tries to find. Bouncing boxes, which delineate the areas of interest inside the image where things are expected to be put, are at the same time reported. The following fundamental stage for successful mathematical registering and

examination is to change the handled information into a NumPy array.

- The subsequent stage is to stack a model that has proactively been prepared utilizing prior data from large datasets. Perusing the pre-prepared model's organization layers, which incorporate learnt highlights and boundaries fundamental for exact article recognizable proof, is one part of this interaction. Moreover, yield layers are extricated to give last expectations and work with proficient item order and insight.
- Moreover, the image and explanation document are included the picture handling pipeline, ensuring careful data for additional examination. In the wake of changing over from BGR to RGB, the variety space is adjusted and a veil is made to cause to notice significant qualities. The picture is then upgraded for extra handling and examination by resizing it. In the powerful climate of independent driving frameworks, this careful picture handling strategy lays the preparation for dependable and exact article acknowledgment, further developing street wellbeing and thinking abilities.

v) Feature extraction:

- The most common way of changing over natural information into mathematical qualities that might be taken care of while keeping the data in the first informational collection is known as element extraction [12]. Contrasted with straightforwardly applying ML to the crude information, it produces prevalent results.

- It is feasible to separate elements naturally or physically [11]:
- To extricate includes physically, one must initially figure out which qualities are relevant to a specific issue, depict those elements, and afterward set up a strategy to remove those highlights. Making instructed decisions about whether characteristics could be useful frequently requires a strong handle of the specific situation or space. Researchers and specialists have dealt with include extraction procedures for text, signals, and pictures for quite a long time. The mean of a window in a sign is an illustration of a fundamental element. Programmed highlight extraction, then again, utilizes deep networks or specific calculations to extricate highlights from signs or pictures without the requirement for human cooperation consequently. At the point when you need to develop ML calculations quick from crude information, this strategy may be very useful. One sort of robotized highlight extraction is wavelet dissipating [11, 12].
- The early layers of deep organizations have basically taken the place of component extraction with the ascent of deep learning, albeit essentially for picture information. Before one can build fruitful prescient models for sign and time-series applications, include extraction keeps on being the principal obstacle that requires an elevated degree of involvement.

vi) Algorithms:

- **CNN:** A convolutional neural network is a kind of neural network planned explicitly for the handling of visual information. With its capacity to independently learn highlights for article and example acknowledgment, it succeeds in picture related undertakings. Convolution, pooling, and completely associated layers are a portion of the connected layers that make up CNNs. These layers are helpful for removing data from pictures and are utilized broadly in PC vision and picture examination. It has been used for include extraction, and an expectation model has been built. CNN [30] was utilized in our review to separate highlights and make expectation models.

```

np.random.seed(1006) # fix seed

model = Sequential()
model.add(Conv2D(filters=64, kernel_size=(3, 3), input_shape=(227, 227, 1), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=128, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(filters=256, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.5))

```

Fig 3 CNN

- **Squeeze net:** A small and compelling CNN engineering for picture order is called SqueezeNet [20]. It is prestigious for its compact size and competitive accuracy, which are achieved by sharp plan choices like as crush and-excitation blocks and 1x1 convolutional filters. This little size functions admirably on gadgets with restricted assets and empowers speedier constant applications. Crush net was utilized in our review to extract includes and make prediction models.


```
def fire_module(x, squeeze, expand):
    y = Conv2D(filters=squeeze, kernel_size=1, activation='relu', padding='same')(x)
    y = BatchNormalization(momentum=0.9999)(y)
    y1 = Conv2D(filters=expand // 2, kernel_size=3, activation='relu', padding='same')(y)
    y1 = BatchNormalization(momentum=0.9999)(y1)
    y2 = Conv2D(filters=expand // 2, kernel_size=1, activation='relu', padding='same')(y)
    y2 = BatchNormalization(momentum=0.9999)(y2)
    return concatenate([y1, y2])

def squeeze_layer(input_shape, num_classes):
    input = Input(shape=input_shape)
    y = Conv2D(kernel_size=7, filters=64, strides=2, padding='same', activation='relu')(input)
    y = BatchNormalization(momentum=0.9999)(y)
    y = MaxPooling2D(pool_size=2, strides=2)(y)
    y = fire_module(y, 32, 64)
    y = fire_module(y, 32, 64)
    y = fire_module(y, 32, 128)
    y = MaxPooling2D(pool_size=2, strides=2)(y)
    y = fire_module(y, 48, 96)
    y = fire_module(y, 48, 96)
    y = fire_module(y, 48, 192)
    y = MaxPooling2D(pool_size=2)(y)
    y = fire_module(y, 64, 128)
    y = Conv2D(kernel_size=1, filters=128, strides=1, padding='same', activation='relu')(y)
    y = GlobalAveragePooling2D()(y)
    y = Dense(num_classes, activation='softmax')(y)
    model = Model(input, y)
    return model
```

Fig 4 Squeeze net

- Alex net:** 2012 saw the triumph of AlexNet, an earth shattering CNN design, in the ImageNet contest. With eight layers absolute — three totally connected and five convolutional — it is deep. [21] ReLU enactment and dropout were first introduced by AlexNet, which was a forward leap in deep learning for picture classification. Because of its prosperity, AI has progressed much farther. We utilized AlexNet to separate elements and make expectation models for our venture.

```
def create_model():
    AlexNet = Sequential()

    #1st Convolutional Layer
    AlexNet.add(Conv2D(filters=64, input_shape=(224,224,3), kernel_size=(11,11), strides=(2,2), padding='same'))
    AlexNet.add(BatchNormalization())
    AlexNet.add(Activation('relu'))
    AlexNet.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))

    #2nd Convolutional Layer
    AlexNet.add(Conv2D(filters=128, kernel_size=(5,5), strides=(1,1), padding='same'))
    AlexNet.add(BatchNormalization())
    AlexNet.add(Activation('relu'))
    AlexNet.add(MaxPooling2D(pool_size=(2,2), strides=(2,2), padding='same'))

    #3rd Convolutional Layer
    AlexNet.add(Conv2D(filters=128, kernel_size=(3,3), strides=(1,1), padding='same'))
    AlexNet.add(BatchNormalization())
    AlexNet.add(Activation('relu'))

    #4th Convolutional Layer
    AlexNet.add(Conv2D(filters=256, kernel_size=(3,3), strides=(1,1), padding='same'))
    AlexNet.add(BatchNormalization())
    AlexNet.add(Activation('relu'))
```

Fig 5 Alexnet

- Random Forest:** A gathering learning framework called Random Forest [44] utilizes numerous choice trees together to give forecasts. Each tree in the forest makes a singular figure about the class; voting or average decides the last estimate. Random Forest is an incredible decision for order

occupations in view of its standing for being strong to overfitting and its ability to deal with high-layered information. It is crucial for this task's utilization of deep learning models' determined qualities for exact cardiovascular anomalies classification.

```
from sklearn.ensemble import RandomForestClassifier
RF_model = RandomForestClassifier(n_estimators = 50, random_state = 42)
RF_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_RF = RF_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_RF = le.inverse_transform(prediction_RF)

rf_acc_xec = accuracy_score(test_labels, prediction_RF)
rf_prec_xec = precision_score(test_labels, prediction_RF, average='weighted')
rf_rec_xec = recall_score(test_labels, prediction_RF, average='weighted')
rf_f1_xec = f1_score(test_labels, prediction_RF, average='weighted')
```

Fig 5 Random forest

- Support Vector Machine (SVM):** Support A powerful supervised learning method for relapse and grouping is called Vector Machine. The objective of SVM is to amplify the edge by finding the hyperplane in the component space that best partitions the different classes. By using bit capabilities, SVM can deal with information that is both direct and non-straight. Its proficiency with high-layered information and its solid speculation to new, untested information are its fundamental benefits. SVM is utilized in this study [17] to further develop heart anomalies identification accuracy significantly further.

```
from sklearn.svm import SVC
svm_model = SVC()
svm_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_svm = svm_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_svm = le.inverse_transform(prediction_svm)

svm_acc_xec = accuracy_score(test_labels, prediction_svm)
svm_prec_xec = precision_score(test_labels, prediction_svm, average='weighted')
svm_rec_xec = recall_score(test_labels, prediction_svm, average='weighted')
svm_f1_xec = f1_score(test_labels, prediction_svm, average='weighted')
```

Fig 6 SVM

- K-Nearest Neighbors (KNN):** For relapse and order, K-Nearest Neighbors is an example based learning strategy. By finding the k-nearest data of interest in the component space and recognizing the greater part class among them, it creates forecasts. KNN is extremely helpful for circumstances including a few classes since it is not difficult to understand and utilize. Also, it can effectively oversee loud information. To ensure solid outcomes in this task, KNN adds one more layer of order [17].

```
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier(n_neighbors=3)
knn_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_knn = knn_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_knn = le.inverse_transform(prediction_knn)

knn_acc_xec = accuracy_score(test_labels, prediction_knn)
knn_prec_xec = precision_score(test_labels, prediction_knn, average='weighted')
knn_rec_xec = recall_score(test_labels, prediction_knn, average='weighted')
knn_f1_xec = f1_score(test_labels, prediction_knn, average='weighted')
```

Fig 7 KNN

- Decision Tree:** A decision tree is a construction that looks like a tree, with every node subbing for a trademark, each branch for a decision rule, and each leaf node for a class name. Recursively isolating the dataset as per educational qualities permits it to make decisions. Decision trees can deal with mathematical and straight out information and are interpretable. With regards to recognizing non-direct relationships in the information, they are exceptionally useful. Decision trees help to further develop the arrangement technique in this task.

```
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(max_depth=30)
dt_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_dt = dt_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_dt = le.inverse_transform(prediction_dt)

dt_acc_xec = accuracy_score(test_labels, prediction_dt)
dt_prec_xec = precision_score(test_labels, prediction_dt, average='weighted')
dt_rec_xec = recall_score(test_labels, prediction_dt, average='weighted')
dt_f1_xec = f1_score(test_labels, prediction_dt, average='weighted')
```

Fig 8 Decision tree

- Naive Bayes:** Naive Bayes is a probabilistic classifier that depends on highlight freedom and depends on the Bayes hypothesis. In view of the probability that a trademark will happen in each class, it decides the likelihood that an information point has a place with that class. Naive Bayes is notable for being not difficult to utilize, speedy, and productive with regards to assignments like spam separating and text order. Naive Bayes is utilized in this task [45] to ensure strength and improve the characterization cycle.

```
from sklearn.naive_bayes import GaussianNB
nb_model = GaussianNB()
nb_model.fit(X_train_feature, y_train) #For sklearn no one hot encoding

prediction_nb = nb_model.predict(X_test_features)
#Inverse le transform to get original label back.
prediction_nb = le.inverse_transform(prediction_nb)

nb_acc_xec = accuracy_score(test_labels, prediction_nb)
nb_prec_xec = precision_score(test_labels, prediction_nb, average='weighted')
nb_rec_xec = recall_score(test_labels, prediction_nb, average='weighted')
nb_f1_xec = f1_score(test_labels, prediction_nb, average='weighted')
```

Fig 9 Naive bayes

- xception:** The Xception model, which means "Extreme Inception," is a deep learning design with an accentuation on picture recognizable proof that was created by Google. It is the model we developed for this task. Its successful depth-wise separable convolutions, which lower computation while expanding execution, make it critical.

Xception is an imperative progression in PC vision deep learning because of its outstanding exactness and flexibility. Xception Algo was used in our exploration to separate highlights and build expectation models.

```
base_model = Xception(weights='imagenet', include_top=False)

# add a global spatial average pooling layer
x = base_model.output
x = GlobalAveragePooling2D()(x)
# let's add a fully-connected layer
x = Dense(1024, activation='relu')(x)

x = Dropout(0.5)(x)
# add a logistic layer -- let's say we have 200 classes
predictions = Dense(200, activation='softmax')(x)

# this is the model we will train
model2 = Model(inputs=base_model.input, outputs=predictions)

model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy', 'f1_score', 'precision', 'recall'])
model2.summary()
```

Fig 10 Xception model

4. EXPERIMENTAL RESULTS

Precision: Precision estimates the level of accurately arranged examples or occurrences among the positive examples. Thusly, coming up next is the recipe to decide the precision:

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} = \frac{TP}{TP + FP}$$

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

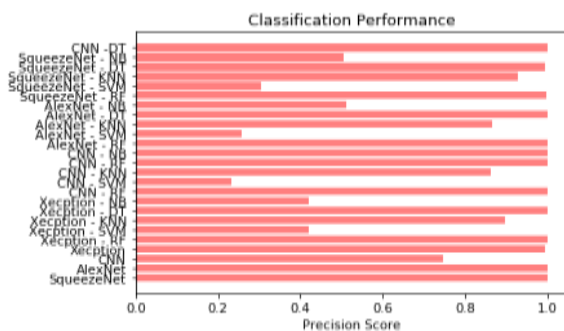


Fig 11 Precision comparison graph

Recall: In machine learning, review is a measurement that evaluates a model's ability to find all relevant occurrences of a given class. It is a proportion of how well a model catches instances of a specific class: the proportion of appropriately anticipated positive perceptions to the all out number of real positives.

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

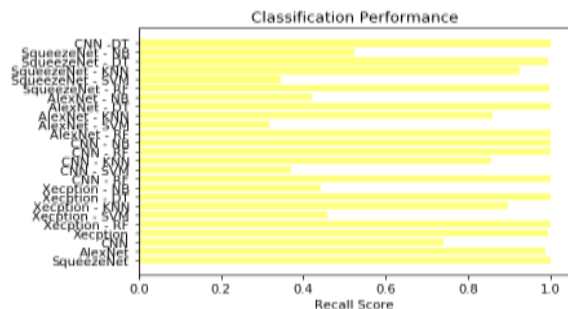


Fig 12 Recall comparison graph

Accuracy: The level of exact expectations spread the word about in a characterization work is as accurate, and it shows how exact a model's forecasts are in general.

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

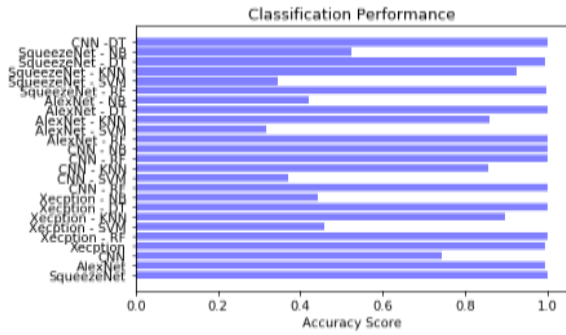


Fig 13 Accuracy graph

F1 Score: The F1 Score is fitting for lopsided datasets on the grounds that it gives a fair metric that considers both misleading up-sides and bogus negatives. It is determined as the consonant mean of accuracy and review.

$$F1\ Score = 2 * \frac{Recall \times Precision}{Recall + Precision} * 100$$

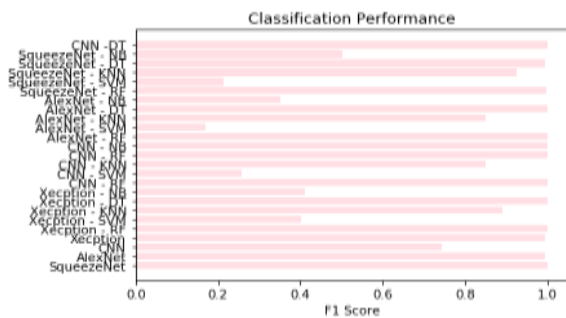


Fig 14 F1Score

#	ML Model	Accuracy	Precision	Recall	F1_score
0	SqueezeNet	1.000	1.000	1.000	1.000
1	AlexNet	0.997	1.000	0.990	0.998
2	CNN	0.742	0.747	0.742	0.743
3	Xception	0.999	0.998	0.998	0.998
4	Xception-BB	1.000	1.000	1.000	1.000
5	Xception-SVM	0.459	0.421	0.418	0.423
6	Xception-KNN	0.898	0.898	0.898	0.898
7	Xception-DT	1.000	1.000	1.000	1.000
8	Xception-BB	0.444	0.421	0.444	0.411
9	CNN-BB	1.000	1.000	1.000	1.000
10	CNN-SVM	0.370	0.322	0.370	0.339
11	CNN-KNN	0.839	0.882	0.818	0.839
12	CNN-BB	1.000	1.000	1.000	1.000
13	CNN-SVM	1.000	1.000	1.000	1.000
14	AlexNet-BB	1.000	1.000	1.000	1.000
15	AlexNet-SVM	0.317	0.237	0.317	0.188
16	AlexNet-KNN	0.881	0.881	0.881	0.881
17	AlexNet-DT	1.000	1.000	1.000	1.000
18	AlexNet-BB	0.420	0.313	0.420	0.313
19	SqueezeNet-BB	0.998	0.998	0.998	0.998
20	SqueezeNet-SVM	0.348	0.302	0.348	0.311
21	SqueezeNet-KNN	0.827	0.828	0.827	0.823
22	SqueezeNet-DT	0.994	0.994	0.994	0.994
23	SqueezeNet-BB	0.523	0.304	0.523	0.303
24	CNN-DT	1.000	1.000	1.000	1.000

Fig 15 Performance Evaluation table

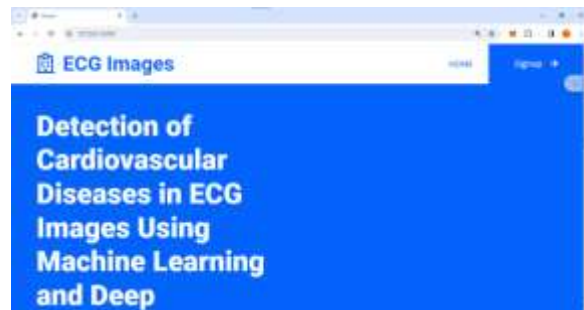
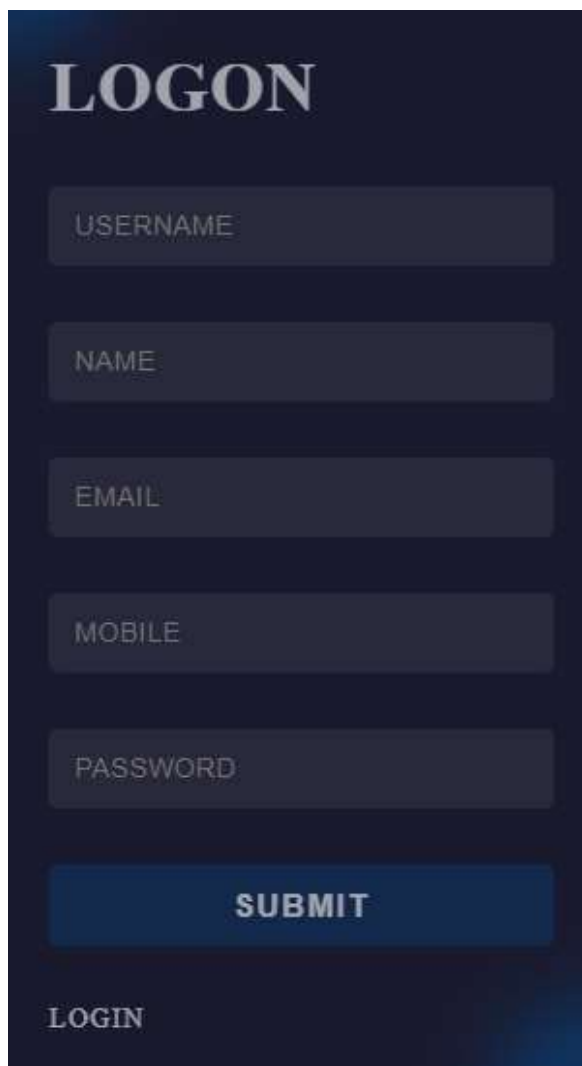


Fig 16 Home page



LOGON

USERNAME

NAME

EMAIL

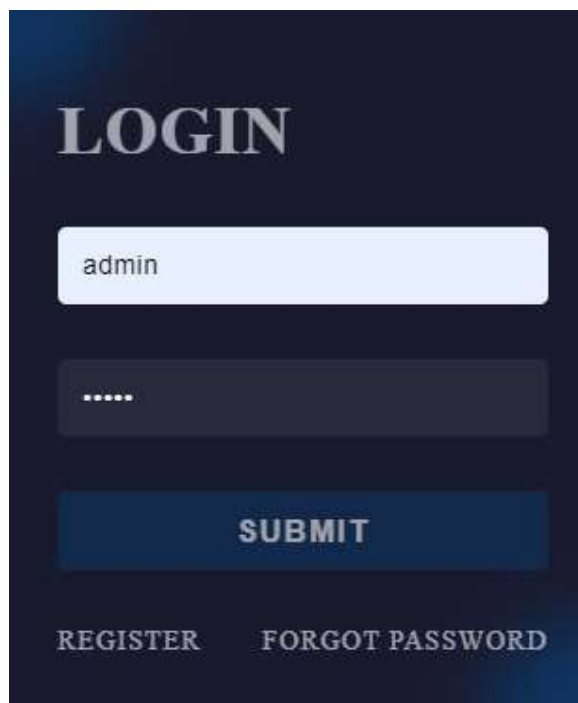
MOBILE

PASSWORD

SUBMIT

LOGIN

Fig 17 Registration page



LOGIN

admin

.....

SUBMIT

REGISTER FORGOT PASSWORD

Fig 17 Login page



Fig 18 Input image folder



Form

Choose File HB(14).jpg Upload

Fig 19 Upload input image



Fig 20 Predict result for given input

5. CONCLUSION

Utilizing deep learning methods, the concentrate effectively endeavored to distinguish critical heart issues utilizing ECG pictures [32]. Unmistakable models, for example, SqueezeNet and AlexNet showed almost perfect arrangement, exhibiting the adequacy of deep learning in delivering exact figures. The addon, Xception, showed exceptional precision in estimating abnormalities in the heart. This exhibits how modern deep learning models might work on demonstrative capacities over traditional strategies. While profound learning models performed particularly well, joining deep learning-based include extraction with regular ML delivered conflicting results. This suggests that deep learning has extraordinary advantages with regards to distinguishing unpredictable examples in ECG pictures [32, 33]. Jar's cooperation with SQLite made ensured that the client testing front-end was protected and simple to utilize. This helpful and safe connection point further develops the client experience and makes it simpler to rapidly test the delivered models. The task's achievements feature man-made intelligence's true capacity, particularly deep learning, for early cardiovascular sickness distinguishing proof. Since it makes brief activities

conceivable, this has significant repercussions for upgrading medical care results. The meaning of using simulated intelligence for early disease determination is stressed in the task's decision. It perceives the progressive impact of new innovation on improving patient results and demonstrative abilities, and it animates more concentrate in this pivotal area of medical services.

6. FUTURE SCOPE

Future examinations could focus on streamlining the hyperparameters of the proposed [33] CNN model to improve its presentation significantly further. The exactness and productivity of the model might be improved by deliberately altering factors like learning rates, clump sizes, and dropout rates. Energizing open doors emerge when the CNN model is integrated into the Industrial Internet of Things (IIoT) space. The model might be changed for an assortment of grouping errands in IIoT applications, for example, oddity identification in modern gear or quality control in assembling processes, as well as anticipating cardiovascular illness. Examining substitute organization plans or additional layers might further develop execution. To additionally work on the [31, 33, 36]CNN model's ability to recognize cardiovascular sicknesses, specialists might take a gander at adding more convolutional or intermittent layers or even inspect state of the art network geographies. Extending the size and assortment of datasets that the framework can deal with can expand its viability. To ensure the generalizability of

the model and its relevance to many cardiovascular sicknesses and patient profiles, this expansion ought to consolidate information from a few sources and populaces.

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