



# Classification of Arrhythmia

## Using Deep Learning

# What is arrhythmia

Definition

Irregular heart  
rhythm

Significance

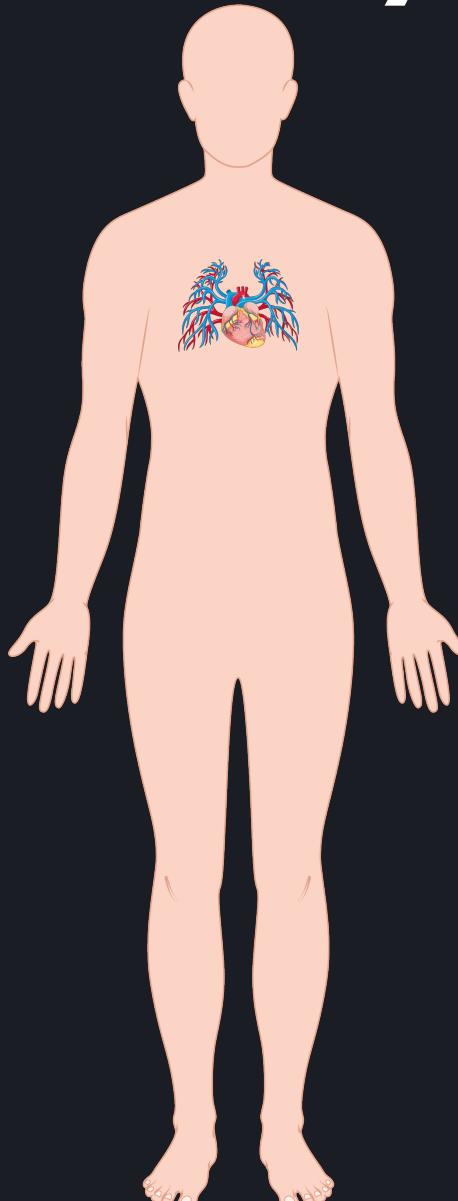
Cardiovascular  
health impact

Importance

Early detection  
and classification

Role of ECG signals

Diagnosis and  
monitoring



## Atrial Arrhythmia

These are irregular heartbeats originating in the heart's upper chambers (atria) and can be caused by various factors. They range in severity and can lead to complications like stroke and heart failure.

## Ventricular Arrhythmia

Ventricular arrhythmias are abnormal heartbeats that originate in your lower heart chambers, called ventricles. These types of arrhythmias cause your heart to beat too fast, which prevents oxygen-rich blood from circulating to the brain and body and may result in cardiac arrest.

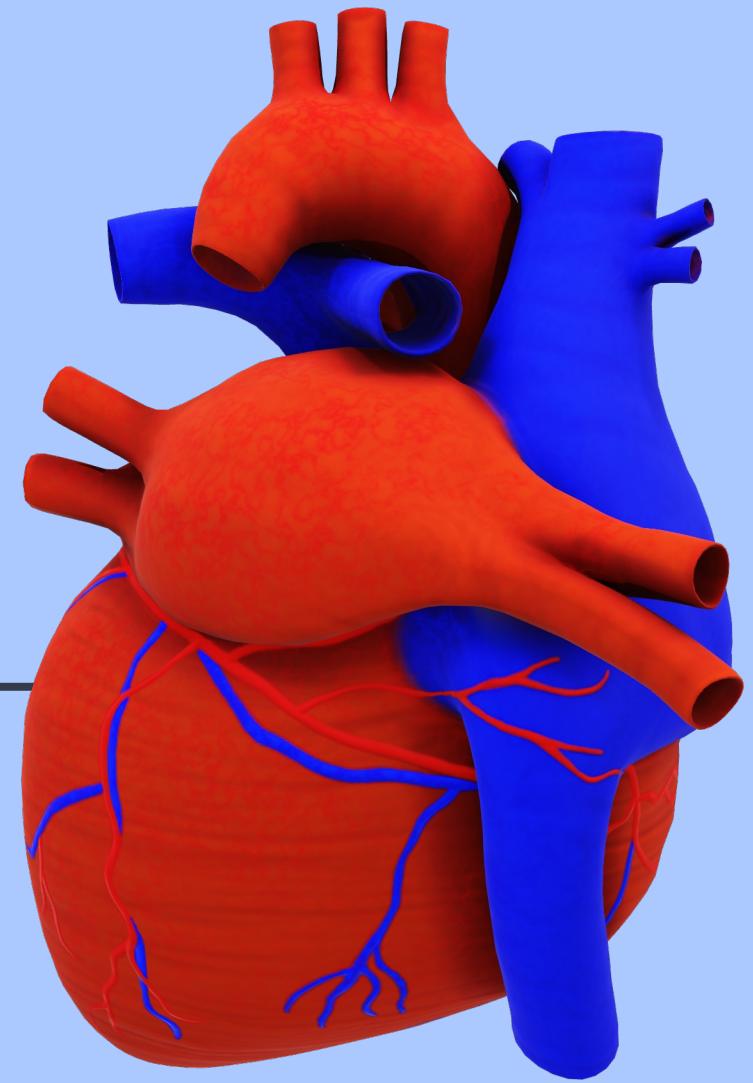
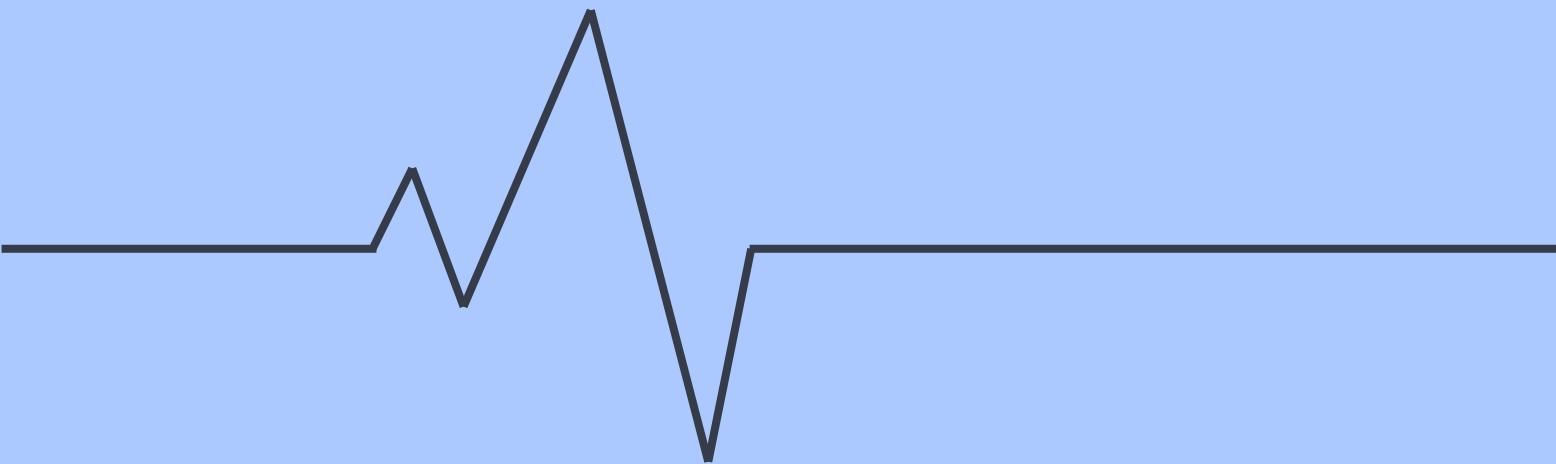
## Bradyarrhythmia

Bradyarrhythmia is an abnormally slow resting heart rate, typically below 60 beats per minute. A too-slow heart rhythm can result from changes in the heart's electrical system, a heart defect or other medical conditions

Atrial Arrhythmia

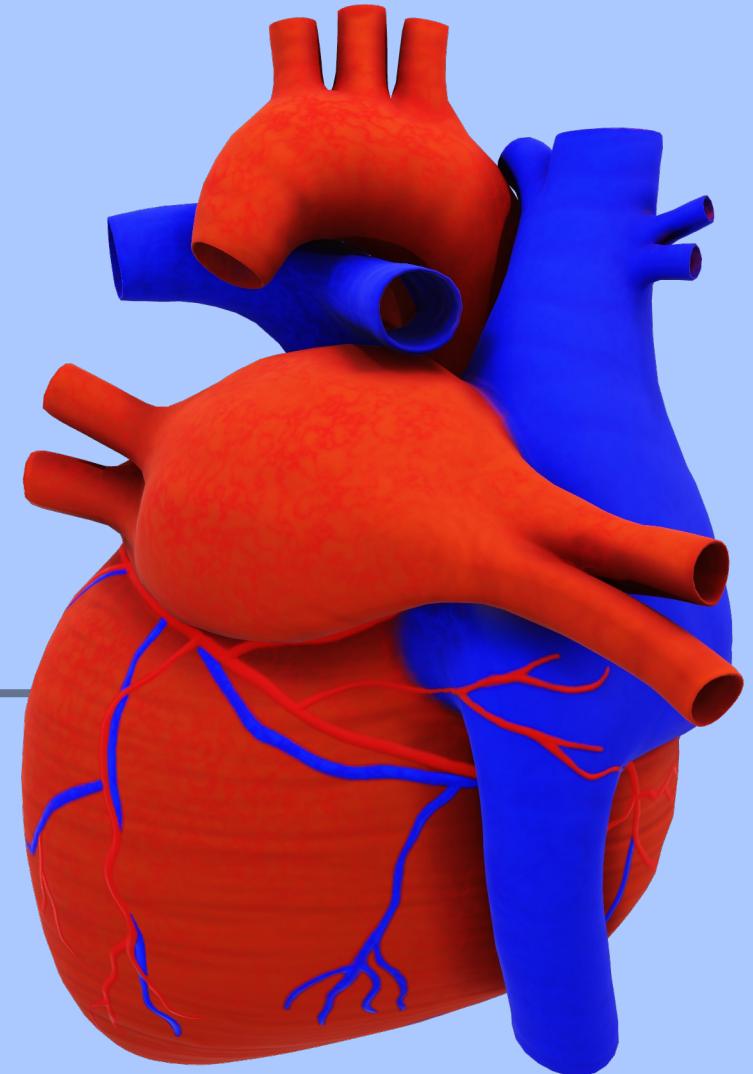
Ventricular Arrhythmia

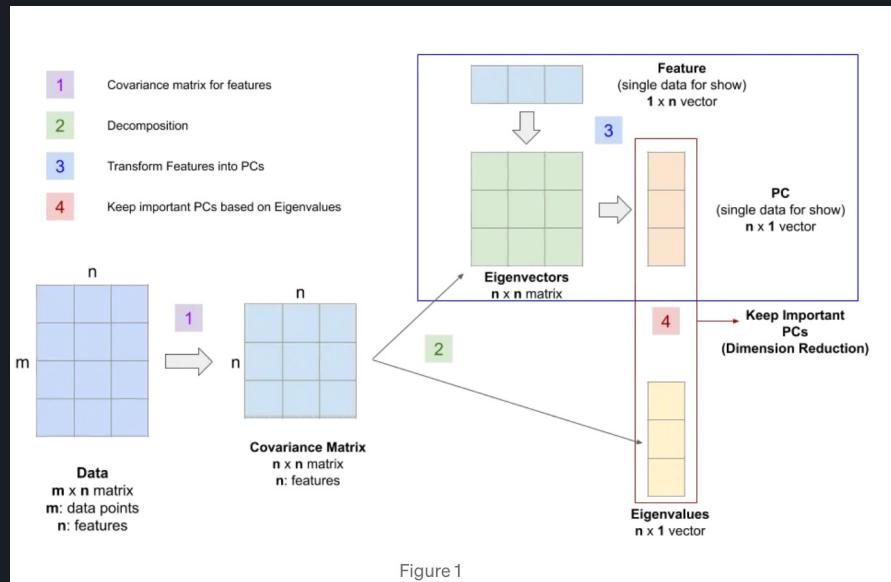
Bradyarrhythmia



# ECG SIGNAL ACQUISITION

- Nerve and muscle cells communicate with electrical and chemical signals.
- The sinoatrial node (SA node) in the right atrium generates electrical signals that control the heartbeat.
- These signals spread through the heart muscle as tiny electrical impulses.
- The impulses cause the atria and ventricles of the heart to contract.
- The spread of signals through the heart can be measured on the skin surface.
- An ECG measures changes in electrical signals/voltage on different areas of the skin.
- The measured signals are plotted as a graph called an electrocardiogram (ECG).

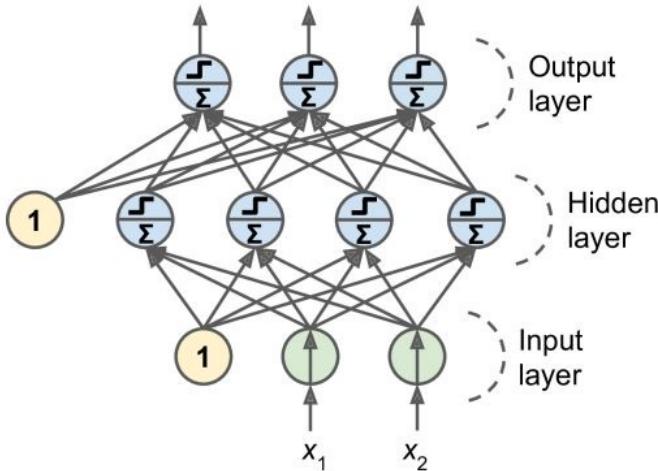




# PCA

Principal Component Analysis (PCA) is a dimensionality reduction technique consisting of four steps: feature covariance, eigen decomposition, principal component transformation, and choosing components based on explained variance. It offers two options for reducing dimensionality: feature elimination and feature extraction using PCA.

# ANN



An MLP (Multilayer Perceptron) is a neural network with input, hidden, and output layers. It can be used for classification tasks. In binary classification, a single output neuron estimates the probability of the positive class. For multilabel binary classification, multiple output neurons are used. In multiclass classification, each class has its own output neuron, and the softmax function ensures valid probabilities. MLPs offer flexibility for different classification scenarios.



# DATASET FEATURES

The first step in our research methodology is to collect a suitable dataset for training and evaluation. In this study, we will utilize the MIT-BIH Arrhythmia Database, which is a widely used dataset containing ECG signals with annotated arrhythmia classes. The dataset consists of records from various patients, providing a diverse range of arrhythmia cases for analysis.



Aspects	Features
N	NORMAL
S	ATRIAL PREMATURE
V	PREMATURE VENTRICULAR CONTRACTION
F	FUSION OF VENTRICULAR AND NORMAL
Q	FUSION OF PACED AND NORMAL
Number of Samples: 87554 Number of Categories: 5 Sampling Frequency: 125Hz	

Classes: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]

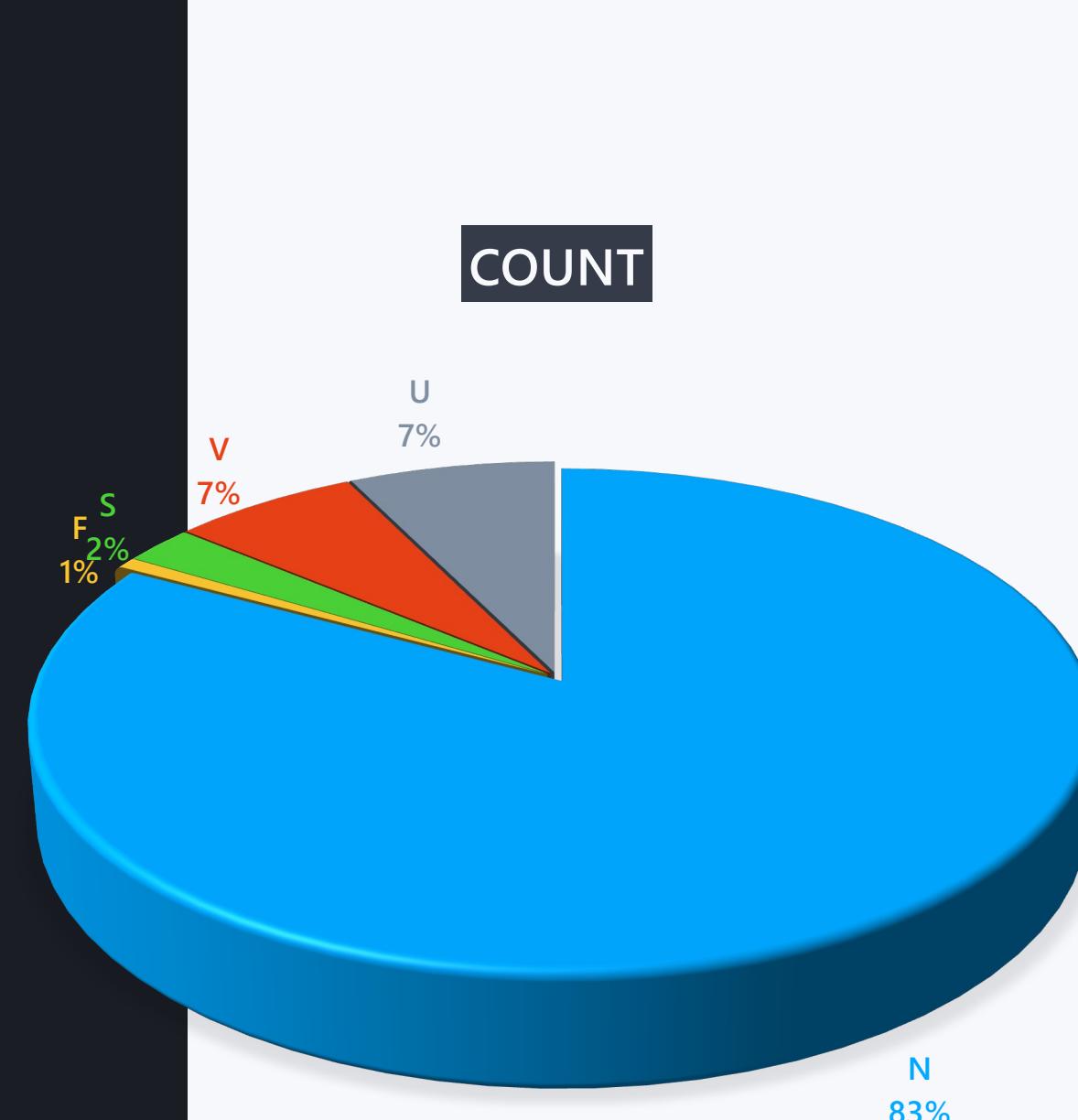
	OUTPUT
COUNT	87554
MEDIAN	0.473376
STD	1.143184
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	4.000000

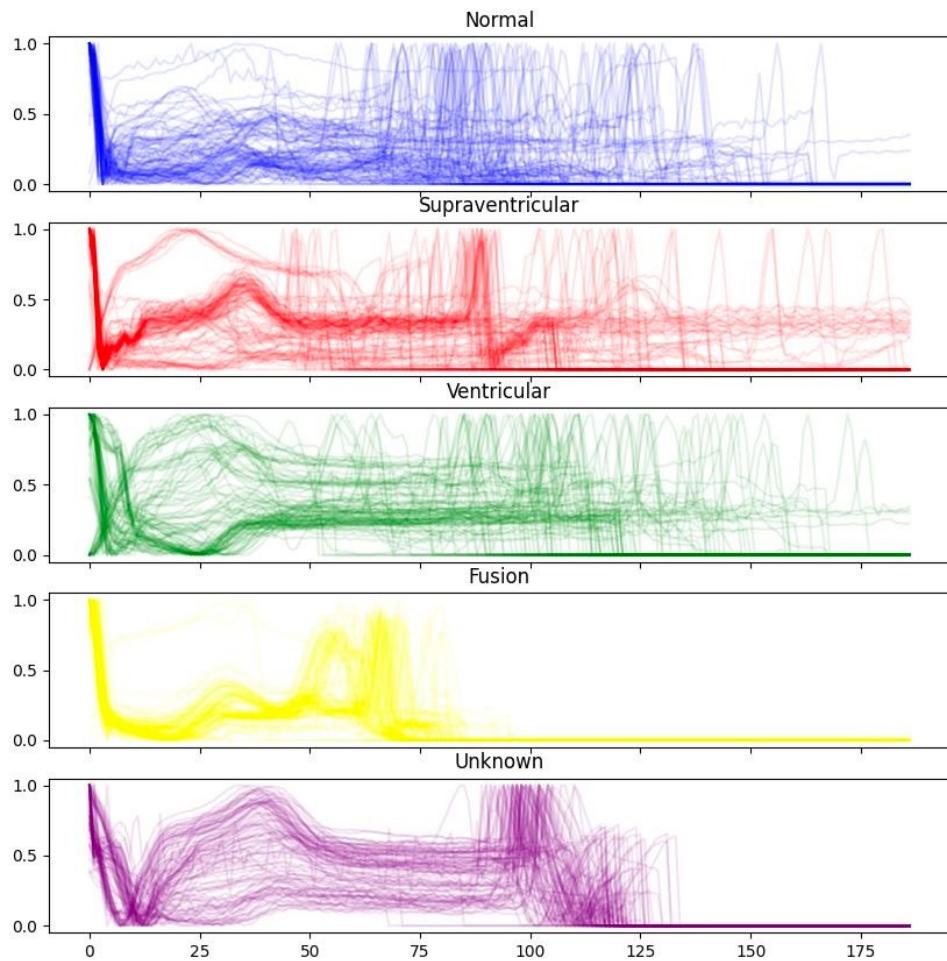
- Regular, right, or left bundle branch block, nodal escape, and atrial escape are all in the “N” category.
- Atrial premature, aberrant atrial premature, nodal premature, and supraventricular premature fall under the “S” category.
- Ventricular escape and premature ventricular contraction are seen in the “V” category.
- Fusion of ventricular and normal is labeled as an “F” class.
- Paced and fusion of paced and normal unclassifiable are labeled as a “Q” class



# DATA PREPROCESSING

The combination of checking for null values, applying PCA, and leveraging data visualization techniques allows us to preprocess the data effectively, reduce dimensionality, and gain insights into the underlying structure of the dataset.





# Data Visualization

By visualizing the first 100 ECG signals, you can observe the density of the signals and potentially identify any patterns, abnormalities, or variations within the dataset. Adjusting the visualization parameters can further enhance your understanding of the density and characteristics of the ECG signals.



# MODEL TRAINING

This code creates a sequential model with two hidden layers and one output layer. The Dense layers represent fully connected layers, and BatchNormalization is used for batch normalization. The model is compiled with the SGD optimizer and sparse categorical cross-entropy loss function. The `model.summary()` function provides a summary of the model's architecture.



```
...  
  
model = Sequential()  
model.add(Flatten(input_shape=X.shape[1:]))  
model.add(Dense(50, kernel_initializer="he_normal",  
               # BatchNormalization())) # Batch normalization layer  
model.add(Dense(50, kernel_initializer="he_normal",  
               # BatchNormalization())) # Batch normalization layer  
model.add(Dense(5, activation="softmax"))  
  
optimizer = optimizers.SGD(learning_rate=1e-2, momentum=0.9)  
model.compile(loss="sparse_categorical_crossentropy",  
              optimizer=optimizer, metrics=["accuracy"])
```

# Model Evaluation

To train a model with data splitting and early stopping, we import necessary libraries such as `StratifiedShuffleSplit` for data splitting and `EarlyStopping` for early stopping. Using `StratifiedShuffleSplit`, we split the data into training and validation sets. We create and compile the model with chosen optimizer, loss function, and metrics. Early stopping is defined with `EarlyStopping`, monitoring validation loss and setting a patience value. We fit the model to the training data, providing validation data and including the early stopping callback. This approach enhances model training with effective data splitting and early stopping.



```
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, valid_index in split.split(df, df[187]):
    X = df.iloc[train_index]
    X_valid = df.iloc[valid_index]

import keras.callbacks
early_stopping_cb = keras.callbacks.EarlyStopping(patience=10,
                                                    restore_best_weights=True)
model.fit(X_train, y_train, epochs=20, validation_data=(X_valid, y_valid),
          callbacks = early_stopping_cb, batch_size=32)
```

# RESULTS

## Test Results

The overall accuracy of the deep learning models for arrhythmia classification was found to be 98%, indicating a high level of accuracy in correctly identifying and

# Without Feature Extraction

	Precision	Recall	F1 Score
0.0	0.98	0.99	0.99
1.0	0.89	0.72	0.80
2.0	0.96	0.93	0.94
3.0	0.85	0.70	0.77
4.0	0.99	0.98	0.98
accuracy			0.98
macro avg	0.93	0.87	0.90
weighted avg	0.98	0.98	0.98

## With Feature Extraction

Test Accuracy

Metrics

Test Results

## Without Feature Extraction

## With Feature Extraction

	Precision	Recall	F1 Score
0.0	0.99	0.99	0.99
1.0	0.88	0.74	0.81
2.0	0.94	0.93	0.94
3.0	0.82	0.72	0.77
4.0	0.98	0.99	0.98
<hr/>			
accuracy			0.98
macro avg	0.92	0.88	0.90
weighted avg	0.98	0.98	0.98

Test Accuracy

Metrics

Test Results

## Without Feature Extraction

## With Feature Extraction

### Test Accuracy

	Precision	Recall	F1 Score
0.0	0.99	0.99	0.99
1.0	0.84	0.73	0.78
2.0	0.95	0.93	0.94
3.0	0.80	0.69	0.74
4.0	0.98	0.98	0.98
<hr/>			
accuracy			0.98
macro avg	0.91	0.86	0.89
weighted avg	0.98	0.98	0.98

### Metrics

### Test Results

## Without Feature Extraction

## With Feature Extraction

### Test Accuracy

### Metrics

Precision :- The fraction of relevant instances among the retrieved instances.

Recall :- The fraction of relevant instances that were retrieved.

F1 Score :- F1 score is a single metric that balances precision and recall to evaluate the overall performance of a classification model.

Accuracy :- Accuracy is a measure of the correctness of a classification model, representing the percentage of correctly predicted instances out of the total instances

### Test Results

The overall accuracy of the deep learning models for arrhythmia classification was

## Without Feature Extraction

## With Feature Extraction

### Test Accuracy

### Metrics

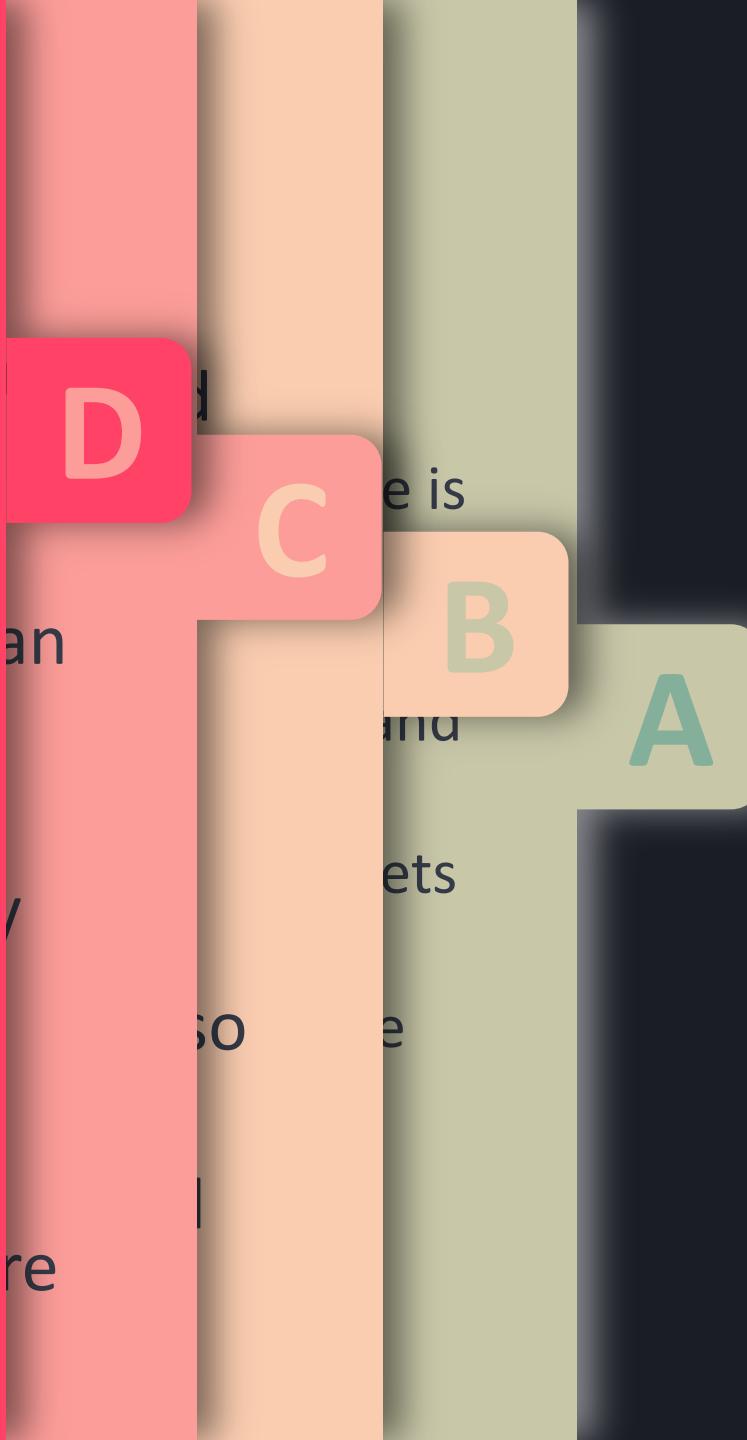
## Test Results

The overall accuracy of the deep learning models for arrhythmia classification was found to be 98%, indicating a high level of accuracy in correctly identifying and classifying arrhythmias based on ECG signals.

The precision, recall, and F1-score for each individual class were also calculated, providing additional insights into the models' performance in correctly classifying each arrhythmia type. The results demonstrate the models' ability to accurately classify different arrhythmia classes based on the extracted features from ECG signals, thus showcasing the potential of deep learning approaches in improving arrhythmia diagnosis and patient care.

# ility and bility

odels often lack transparency which may limit their use in clinical settings. Researchers should focus on developing methods to interpret the complex decisions made by machine learning techniques such as gradient-based methods, saliency maps, and feature visualization. These approaches can help provide insights into the decision-making reasoning and behavior of machine learning models in healthcare.



## Future Prospects

- DATASET EXPANSION
- ENSEMBLE APPROACHES
- REAL TIME MONITORING AND DECISION SUPPORT
- INTERPRETABILITY AND EXPLAINABILITY



## DISCUSSION

Our study demonstrates the effectiveness of deep learning models for arrhythmia classification using ECG signals. By employing feature extraction techniques like PCA, we improved accuracy in identifying different arrhythmia types. The models achieved high accuracy in classifying normal ECG signals and showed promise in detecting specific arrhythmias. However, interpretability and generalizability remain challenges. Further research is needed to address these concerns.

## CONCLUSION

Our study demonstrates the potential of deep learning models for accurate arrhythmia classification using ECG signals. Feature extraction techniques, such as PCA, enhance classification accuracy. Further research is needed to validate findings on larger datasets and improve interpretability. Integration of deep learning techniques can enhance arrhythmia diagnosis and patient care.

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Thank you

