

I. INTRODUCTION

Electrocardiogram (ECG) signals are widely used to monitor heart activity and help doctors detect heart rhythm problems. Accurate ECG classification is important for identifying abnormal heartbeats and supporting early medical diagnosis. However, analyzing ECG signals manually can be difficult and time-consuming, especially when large amounts of data are involved.

In recent years, Convolutional Neural Networks (CNNs) have become a popular method for automatic ECG classification. CNN models can learn important patterns directly from raw ECG signals without the need for manual feature extraction. In particular, one-dimensional CNNs (1D CNNs) are well suited for ECG data because they can effectively capture changes in the signal over time, such as the shape of heartbeats and rhythm variations.

This study uses a 1D CNN model to classify ECG heartbeats into different categories. The goal is to improve classification accuracy and provide a reliable automated approach for analyzing ECG signals. By using deep learning techniques, this method aims to support healthcare professionals and contribute to faster and more accurate heart disease detection.

II. DATA EXPLORATION

The ECG heartbeat dataset contains a total of 109,446 samples, with 87,554 samples used for training and 21,892 samples for testing. Each sample consists of 187 features, representing the amplitude values of an ECG signal over time, followed by a class label indicating the heartbeat type. The dataset includes five classes: **Normal**, **Supraventricular**, **Ventricular**, **Fusion**, and **Unknown**.

An analysis of the class distribution shows a strong class imbalance. Normal heartbeats dominate the dataset, accounting for approximately 82.8% of the training samples. In contrast, abnormal classes such as Supraventricular (2.5%) and Fusion (0.7%) are significantly underrepresented. This imbalance is also reflected in the test set and presents a challenge for model training, as the classifier may become biased toward the majority class.

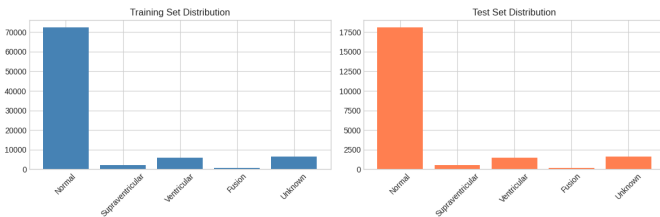


Fig. 1. Data distributed plot

To better understand the data, representative ECG signals from each class were visualized. The plots show clear differences in waveform morphology between heartbeat types, particularly around the QRS complex. An ECG heartbeat is composed of characteristic waveform components, including the P wave, QRS complex, and T wave, each representing a

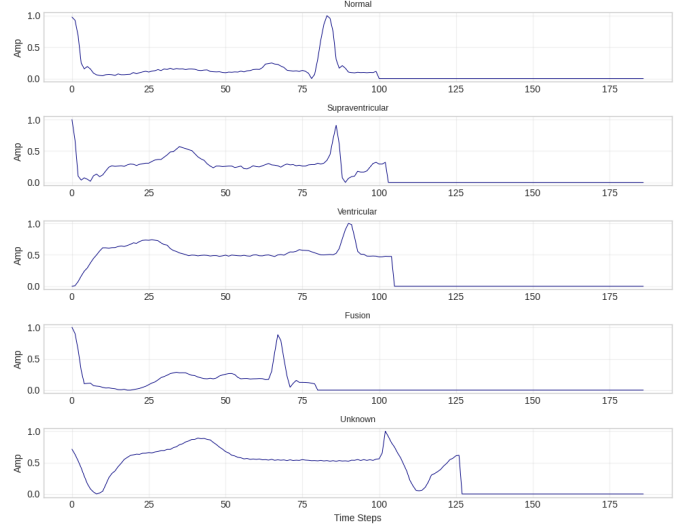


Fig. 2. ECG Heartbeat Wavelength

specific electrical activity of the heart. In the analyzed dataset, each heartbeat is sampled over 187 time steps, allowing the temporal structure and wavelength of these components to be observed and compared across different classes.

For normal heartbeats, the waveform shows a regular and consistent pattern with a narrow QRS complex and smooth transitions between peaks. The wavelength between successive peaks remains relatively stable, indicating a healthy and synchronized electrical conduction. The amplitude rises sharply during the QRS complex, followed by a gradual return to baseline.

In contrast, supraventricular beats display noticeable variations in wavelength and shape. The QRS complex often appears slightly wider or less pronounced, and the distance between waveform peaks is less uniform. These changes reflect irregular electrical signals originating above the ventricles, leading to altered conduction timing.

Ventricular heartbeats show the most distinct wavelength differences. The QRS complex is typically wider and more dominant, indicating slower and abnormal ventricular activation. The extended wavelength and higher amplitude make ventricular beats easier to distinguish from normal rhythms but also more critical for accurate detection.

Fusion beats combine characteristics of both normal and ventricular beats. Their waveforms present intermediate wavelengths and mixed morphological features, resulting in irregular peak spacing and reduced clarity of individual waveform components. This overlap makes fusion beats particularly challenging to classify.

The unknown class demonstrates high variability in both wavelength and amplitude. Some signals exhibit prolonged or distorted waveform segments, while others show irregular peak spacing or noise. This diversity suggests heterogeneous underlying patterns, increasing classification difficulty.

Overall, the observed differences in wavelength, peak spac-

ing, and waveform width across classes highlight the importance of temporal feature learning. These characteristics justify the use of a 1D CNN, which can effectively capture local wavelength patterns and morphological variations along the time axis, enabling more accurate ECG heartbeat classification.

III. DATA PREPARATION

```

1 X_train_resaped = X_train.reshape(X_train.
   shape[0], X_train.shape[1], 1)
2 X_test_resaped = X_test.reshape(X_test.shape
   [0], X_test.shape[1], 1)
3
4 y_train_encoded = tf.keras.utils.
   to_categorical(y_train, num_classes=5)
5 y_test_encoded = tf.keras.utils.
   to_categorical(y_test, num_classes=5)

```

Listing 1. Reshaping and encoding ECG data for CNN input

Before training the convolutional neural network, the ECG data were preprocessed to match the input requirements of a one-dimensional CNN. Each ECG sample originally consists of 187 time-step values, representing the amplitude of the heartbeat signal over time. Since CNN models require an explicit channel dimension, the input data were reshaped from a two-dimensional format to a three-dimensional format of (samples, time steps, channels). As a result, the training and test sets were reshaped to (87,554, 187, 1) and (21,892, 187, 1) respectively, where the single channel represents the ECG signal amplitude.

TABLE I
SHAPES OF THE ECG DATASETS AFTER RESHAPING AND LABEL ENCODING

Dataset	Shape
Training data	(87,554, 187, 1)
Test data	(21,892, 187, 1)
Training labels (one-hot)	(87,554, 5)
Test labels (one-hot)	(21,892, 5)

The class labels were then converted from integer values to one-hot encoded vectors using categorical encoding. This transformation allows the model to treat the classification task as a multi-class problem and is required when using a softmax output layer with categorical cross-entropy loss. After encoding, the training labels had a shape of (87,554, 5) and the test labels had a shape of (21,892, 5), corresponding to the five heartbeat classes.

```

1 from sklearn.model_selection import
   train_test_split
2
3 X_train_split, X_val_split, y_train_split,
   y_val_split = train_test_split(
4     X_train_resaped,
5     y_train_encoded,
6     test_size=0.2,
7     random_state=42
8 )

```

Listing 2. Splitting the training data into training and validation sets

TABLE II
TRAINING AND VALIDATION SET SIZES AFTER DATA SPLITTING

Subset	Shape
Training set	(70,043, 187, 1)
Validation set	(17,511, 187, 1)
Training labels	(70,043, 5)
Validation labels	(17,511, 5)

To enable model validation during training, the reshaped training data were further divided into a training subset (80%) and a validation subset (20%) using a random split. This resulted in 70,043 samples for training and 17,511 samples for validation. The validation set was used to monitor model performance and detect overfitting during training, while the test set was kept separate for final evaluation.

This preprocessing pipeline ensures that the ECG signals are correctly structured for CNN input, that class labels are properly represented for multi-class classification, and that model performance can be reliably assessed during training.

IV. CNN MODEL

```

model = models.Sequential([
    layers.Conv1D(filters=64, kernel_size=5,
        activation='relu',
        input_shape=X_train_split.
            shape[1:]),
    layers.MaxPooling1D(pool_size=2),

    layers.Conv1D(filters=128, kernel_size=5,
        activation='relu'),
    layers.MaxPooling1D(pool_size=2),

    layers.Dropout(0.3),
    layers.Flatten(),

    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),

    layers.Dense(num_classes, activation='
        softmax')
])

```

Listing 3. Proposed 1D CNN architecture for ECG heartbeat classification

The proposed model is a one-dimensional convolutional neural network (1D CNN) designed for ECG heartbeat classification. The network begins with two convolutional layers that apply temporal filters along the ECG signal to extract meaningful waveform features. The first convolutional layer uses 64 filters to capture basic patterns such as edges and short-term signal changes, while the second layer increases the number of filters to 128, allowing the model to learn more complex heartbeat characteristics.

Each convolutional layer is followed by a max-pooling operation, which reduces the temporal resolution and helps the model focus on the most important features while decreasing computational cost. Dropout layers with a rate of 0.3 are applied to reduce overfitting by randomly disabling neurons during training. After feature extraction, the flattened feature vector is passed to a fully connected layer with 128 neurons,

enabling higher-level representation learning. The final softmax layer outputs class probabilities for the five heartbeat categories.

Overall, this architecture effectively balances model complexity and computational efficiency. By learning local temporal patterns directly from raw ECG signals, the model is well suited for distinguishing between normal and abnormal heartbeats, even in the presence of class imbalance. The model

TABLE III
ARCHITECTURE SUMMARY OF THE PROPOSED 1D CNN MODEL

Layer	Output Shape	Parameters
Conv1D (64 filters, kernel 5)	(183, 64)	384
MaxPooling1D (pool size 2)	(91, 64)	0
Conv1D (128 filters, kernel 5)	(87, 128)	41,088
MaxPooling1D (pool size 2)	(43, 128)	0
Dropout (0.3)	(43, 128)	0
Flatten	5,504	0
Dense (128 units)	128	704,640
Dropout (0.3)	128	0
Dense (5 units, Softmax)	5	645
Total parameters		746,757

is compiled using the Adam optimizer with categorical cross-entropy loss, which is appropriate for a multi-class ECG classification problem. Accuracy is used as the evaluation metric during training.

Two callbacks are applied:

EarlyStopping monitors validation loss and restores the best weights, helping prevent overfitting.

ReduceLROnPlateau lowers the learning rate when validation loss stops improving, allowing the model to converge more smoothly.

The model is trained for up to 50 epochs with a batch size of 32, using a validation split derived from the training data. This setup ensures that training progress is continuously evaluated on unseen validation samples. Predicted class labels are obtained after 50 epochs with the overall test accuracy is 98.45%, which indicates strong global performance. However, this value mainly reflects performance on the dominant class

V. EVALUATION

A. Analysis of Classification

TABLE IV
CLASSIFICATION PERFORMANCE OF THE CNN MODEL ON THE TEST SET

Class	Precision	Recall	F1-score	Support
Normal	0.99	1.00	0.99	18,118
Supraventricular	0.91	0.75	0.82	556
Ventricular	0.97	0.94	0.96	1,448
Fusion	0.85	0.75	0.80	162
Unknown	0.99	0.99	0.99	1,608
Accuracy		0.98		21,892
Macro Avg	0.94	0.89	0.91	21,892
Weighted Avg	0.98	0.98	0.98	21,892

The classification report highlights clear differences in performance across heartbeat classes. Normal beats achieve very high precision and recall (approximately 0.99–1.00), indicating that the model can identify normal heartbeats with excellent

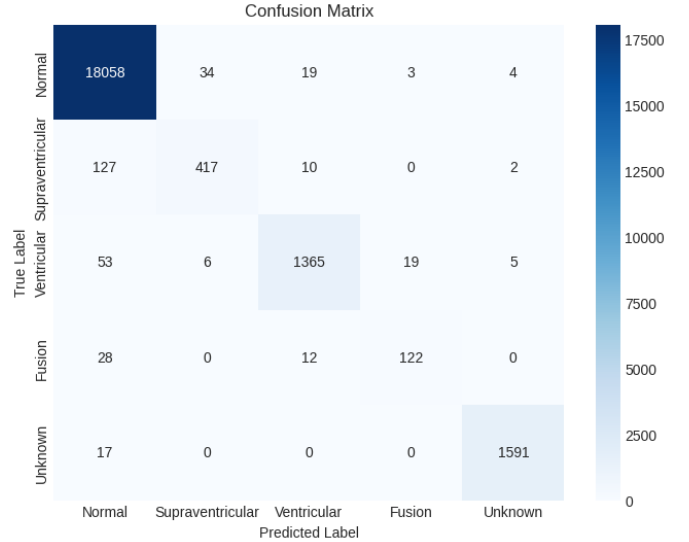


Fig. 3. Confusion Matrix

reliability. Ventricular beats also demonstrate strong performance, with a precision of 0.97 and a recall of 0.94, suggesting effective detection of this clinically important abnormality. In contrast, Supraventricular and Fusion beats exhibit lower recall and F1-scores, which implies that a considerable proportion of these abnormal beats are misclassified or confused with other classes. Unknown beats are classified with near-perfect precision and recall, showing robust recognition by the model. Furthermore, the macro-averaged metrics are noticeably lower than the weighted averages, reflecting uneven performance across different classes and confirming that the overall effectiveness of the model varies depending on the type of heartbeat.

B. Analysis of the Confusion Matrix

The confusion matrix provides a detailed view of how the CNN model performs across different heartbeat classes and where misclassifications occur.

Normal beats are classified extremely well. Out of all Normal samples, 18,058 are correctly predicted, with only a very small number misclassified as Supraventricular (34), Ventricular (19), Fusion (3), or Unknown (4). This confirms the very high recall for the Normal class and shows that the model has learned a strong representation of normal ECG patterns.

For Supraventricular beats, the model correctly identifies 417 samples, but a notable number (127) are misclassified as Normal. This explains the lower recall for this class and suggests that supraventricular beats share waveform characteristics with normal beats, making them harder to distinguish. Ventricular beats show strong performance, with 1,365 correctly classified samples. However, some ventricular beats are confused with Normal (53) and Fusion (19), indicating partial overlap in morphological features, especially around the QRS complex. The Fusion class is the most challenging. Although

122 samples are correctly classified, several are misclassified as Normal (28) or Ventricular (12). This is expected, as fusion beats combine characteristics of both normal and abnormal rhythms, increasing ambiguity. Unknown beats are classified very accurately, with 1,591 correct predictions and only a small number misclassified as Normal (17). This aligns with the high precision and recall observed in the classification report.

Overall, the confusion matrix confirms that the model performs very well on dominant and clearly defined classes (Normal and Unknown), while performance decreases for minority and morphologically similar classes such as Supraventricular and Fusion. This imbalance and feature similarity are the primary sources of classification errors in the model.

VI. CONCLUSION

This study presented a one-dimensional convolutional neural network (1D CNN) for automatic ECG heartbeat classification using a multi-class ECG dataset. Through detailed data exploration, it was shown that the dataset is highly imbalanced, with normal heartbeats dominating both the training and test sets. Despite this challenge, the proposed CNN model was able to learn meaningful temporal features directly from raw ECG signals.

Experimental results demonstrate that the model achieves a high overall test accuracy of 98.45%, indicating strong global performance. Class-wise evaluation reveals excellent recognition of Normal, Ventricular, and Unknown heartbeats, with high precision and recall values. However, performance is noticeably lower for Supraventricular and Fusion beats, as reflected by reduced recall and F1-scores. Analysis of the confusion matrix confirms that these classes are frequently misclassified as Normal or Ventricular, which can be attributed to waveform similarity and limited sample size.

Overall, the results show that 1D CNNs are effective for ECG heartbeat classification and can successfully capture important temporal and morphological characteristics of ECG signals. Nevertheless, the uneven performance across classes highlights the impact of class imbalance and waveform overlap. Future work could focus on improving minority class detection through advanced loss functions, data augmentation, or alternative architectures, with the aim of enhancing clinical reliability for rare but critical heartbeat abnormalities.