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Smarter Classification: Optimizing Feature Engineering and Deep Learning for Imbalanced Datasets

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Abstract - This study sought to compare the effectiveness of two leading machine learning techniques for solving classification problems: feature engineering-based learning and deep learning. The feature engineering approach focused on selecting and calculating important features, while the deep learning approach worked directly with raw signals without additional preprocessing. The comparison was performed on a case study dataset with imbalanced classes. For the feature engineering method, the best model was the XGBoost classifier trained on randomly oversampled data, achieving an average F1 score of 77%. A cost-sensitive version of XGBoost produced a slightly lower average F1 score of 75%. In contrast, the deep learning approach, using a 1D Convolutional Neural Network (CNN), outperformed the other models with an average F1 score of 80%. The results indicate that the features extracted automatically by the CNN's convolutional layers were more relevant for classification than those manually calculated through expert knowledge.

Keywords - Machine Learning, Feature Extraction, Deep Learning, XGBoost, 1D CNN, Classification, Imbalanced Datasets, Ensemble Methods.

I. INTRODUCTION

Classification tasks are a fundamental area of focus in machine learning, with applications across various sectors, including healthcare, finance, and industry [1-2]. Two primary approaches have emerged for addressing these challenges: feature engineering-based learning and deep learning. The feature engineering approach involves manually selecting and extracting features from the data, typically using expert knowledge. These extracted features are then fed into traditional machine learning models, such as decision trees, support vector machines, or ensemble methods like XGBoost [3-4]. In contrast, deep learning models, including Convolutional Neural Networks (CNNs), automatically learn hierarchical features from raw data, often requiring little to no preprocessing [5-6]. This capability for automated feature extraction has been particularly advantageous for unstructured data such as images, signals, and text [7-8].

The choice of the appropriate method depends on several factors, including the type of data, the level of domain expertise, and available computational resources. Feature engineering-based approaches are often preferred when interpretability and domain knowledge are crucial in solving the problem. However, these approaches require considerable time and effort to select the most relevant features and may not always capture the full complexity of the data. In contrast, deep learning models, although more computationally demanding, can automatically detect and utilize complex features, often achieving better performance, particularly for large-scale and high-dimensional datasets [9-10].

This study seeks to conduct a comparative analysis of two approaches using a classification task involving imbalanced data. Specifically, we assess the performance of an XGBoost classifier with manually engineered features and compare it with a 1D Convolutional Neural Network trained on raw signals. Through this analysis, we aim to determine which approach yields better results and explore potential improvements for both methods. Additionally, this study investigates the possibility of combining these techniques into a hybrid model to capitalize on the strengths of both approaches.

II. LITERATURE REVIEW

In the study presented in [11], the authors introduce FaFCNN, a framework based on feature fusion using neural networks for disease classification. The key contribution of this research is the creation of a method that combines multiple types of features, including clinical data and imaging information, to enhance the accuracy of disease classification tasks. The approach utilizes feature fusion, enabling the neural network to process various input sources simultaneously, which improves generalization and overall performance. The framework was tested on several disease datasets, demonstrating notable improvements in classification performance over traditional models. This research emphasizes the potential of feature fusion to enhance the robustness of deep learning models, particularly in complex medical fields characterized by data heterogeneity.

This study [12] investigates a novel method for classifying integers based on residue classes using contemporary deep learning techniques. The authors concentrate on an optimization strategy that leverages residue classes to efficiently classify integers, a relatively unconventional approach in machine learning literature. The paper introduces a deep learning-based framework that automatically extracts relevant features from integer data by converting them into residue classes, improving the model's capability

to handle large-scale datasets. The proposed method surpasses traditional machine learning models in both accuracy and computational efficiency. This research highlights the potential of deep learning in specialized fields like number theory and discrete mathematics.

In this paper [13], Adaptive Ensemble Learning (AEL) is presented as an advanced method for enhancing the performance of deep neural networks (DNNs). The author focuses on improving DNN performance through intelligent feature fusion, integrated within an ensemble learning framework. AEL uses multiple base learners to generate varied feature representations, which are then combined to offer a more comprehensive understanding of the data. This technique has been shown to enhance the model's accuracy by addressing the drawbacks of individual neural networks, such as overfitting and limited generalization. The study's findings emphasize that combining ensemble learning with adaptive feature fusion presents a promising approach for improving DNN-based classifiers in areas like pattern recognition and image processing.

This paper [14] compares two methods—feature-engineering and feature-learning—for classifying multilingual translationese. The study focuses on differentiating translated text from non-translated text across various languages. The feature-engineering method relies on manually designed features based on linguistic and syntactic characteristics, while the feature-learning method utilizes deep learning models to automatically extract features from raw text data. The comparison shows that the feature-learning approach, particularly with convolutional neural networks (CNNs) and recurrent neural networks (RNNs), outperforms traditional feature-engineering models in terms of classification accuracy. However, the study also addresses the challenges of training deep learning models with multilingual data, such as the requirement for large, balanced datasets. This research highlights the increasing significance of end-to-end deep learning models in natural language processing tasks.

This study [15] presents a case study on malware classification using a hybrid approach that integrates feature engineering and deep learning. The authors suggest that combining traditional feature engineering techniques, such as opcode frequency and API call sequences, with deep learning methods can greatly enhance malware detection performance. The approach merges manually crafted features with those learned by deep learning models to capitalize on the advantages of both techniques. The case study shows that the hybrid model outperforms models based solely on feature engineering or deep learning. This research has significant implications for cybersecurity, particularly in detecting new and unknown malware variants, where deep learning alone may face challenges due to limited data.

III. METHODOLOGY

The dataset used for this study was obtained from the 2017 PhysioNet cardiology scientific computing challenge. It comprises 8,528 single-lead ECG signal recordings, with durations ranging from 9 seconds to just over 60 seconds. The data is divided into four distinct classes: Standard, representing signals from healthy patients; AF, indicating patients with atrial fibrillation; Other, containing signals from patients with irregular rhythms that do not fall into the AF category; and Noisy, representing signals that are unclear or unidentifiable. An initial analysis of the dataset revealed an imbalance, with the majority of signals belonging to the Standard and Other categories, while the AF and Noisy classes have much smaller proportions. This imbalance was further highlighted through a visualization in Figure 1, which shows the distribution of data across the different classes.

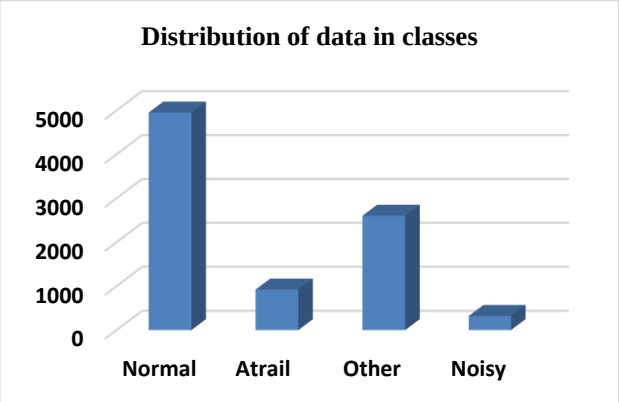

Fig. 1. Distribution of data in the classes

The signals in the dataset were preprocessed by normalizing their amplitude and organizing them for easier manipulation. Feature engineering was then applied to reduce the problem's dimensionality and extract key information for classification. This process involved identifying the P, Q, R, S, and T waves in the signals using the Neurokit2 and BioSPPy libraries. A total of 56 descriptors were extracted, which were grouped into four categories:

• **Medical domain descriptors:** These included the amplitudes of the P, Q, S, and T waves, the P-to-R wave ratio (important for detecting atrial fibrillation), and the mean durations and standard deviations of critical intervals like QRS, ST, and QT. Heart rate metrics, including maximum, minimum, and average values, were also included, along with statistical descriptors such as mean, median, standard deviation, and kurtosis.

• **Temporal characteristics:** These descriptors, derived from heart rate variability, were obtained using Neurokit2 and included metrics like RMSSD, meanNN, SDNN, SDSD, CVNN, CVSD, and pNN20, pNN50.

• **Geometric features:** These descriptors analyzed the non-linear characteristics of RR intervals, including TINN, HTI, and indices from the Poincaré plot, such as SD1, SD2, and the SD1/SD2 ratio.

• **Time-frequency characteristics:** These were

derived from the discrete wavelet transform of the signals, with standard deviations of the approximation and detail coefficients across 8 levels. The Daubechies 6 wavelet was chosen due to its similarity to the QRS complex in ECG signals.

After reducing the original dataset to the 56 descriptors collected in the first stage, five different models were trained to evaluate their performance. These models included Support Vector Machine (SVM), Multinomial Logistic Regression, Random Forest, XGBoost, and Multilayer Perceptron. Each model was assessed based on its accuracy in classifying the ECG signals, offering a comprehensive comparison of their effectiveness with the extracted features. The results from these models were analyzed to determine the most suitable approach for the classification task at hand.

IV. RESULTS ANALYSIS

Figure 2 provides a summary of the average performance in terms of precision, recall, and F1 score for each of the five trained models, using the descriptors gathered during the feature engineering phase. It is evident that the logistic regression and XGBoost classifiers performed the best when considering all metrics. However, when evaluating the performance for each class, as shown in Tables 1 and 3, it is concluded that XGBoost is the top classifier. This is because it achieves excellent results for the first three classes (normal, atrial fibrillation, and other), which are the most crucial for pathology detection. The noisy class is considered a marker of (rare) errors during the examination process. Additionally, XGBoost is deemed the most suitable model in this context, as it is based on decision trees, with added optimization elements that have enhanced its utility since its introduction. The flow of information in decision trees closely mirrors how doctors assess diseases and diagnose patients.

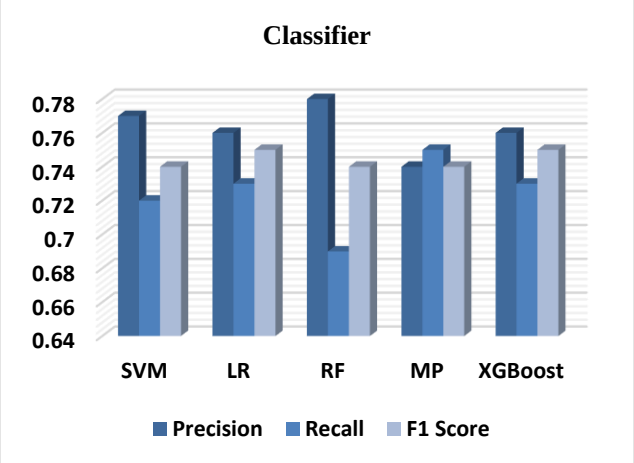

Fig. 2. Average metrics for each trained classifier

A. Addressing Class Imbalance

As mentioned in section IV-A, there is a significant imbalance between the classes in this problem. Several techniques can be used to address this issue, and in this study, two common approaches were employed: class oversampling and cost-sensitive classification.

B. Oversampling

Oversampling involves generating new instances of the minority classes in the training set, allowing the algorithm to learn more about those classes. Various oversampling methods exist, including random oversampling, SMOTE, ADASYN, and others. Random oversampling replicates data from the minority classes randomly. While this method does not result in the loss of any data, it may increase the risk of overfitting since the same information is repeated. SMOTE, in contrast, creates synthetic examples using the k-nearest neighbors algorithm, while ADASYN generates synthetic data based on extreme observations (border points). For this study, random oversampling was chosen for its simplicity. Additionally, classes 2, 3, and 4 were oversampled to an optimal amount, which was determined through a search, ensuring the imbalance was still present but less pronounced. Classes with an equal number of instances were not oversampled to avoid overfitting. The optimal oversampling amounts were determined as follows:

- Class 2: between 600 and 2000
- Class 3: between 2100 and 3500
- Class 4: between 300 and 500

The optimal oversampling was determined by maximizing the F1 score. Based on this, the classes were oversampled to 1600, 3400, and 300 instances, respectively. The classification results for the XGBoost model trained with the oversampled dataset are shown in Table 1 and Figure 3.

TABLE I. CLASSIFICATION REPORT FOR XGBOOST CLASSIFIER TRAINED ON OVERSAMPLED DATA

Class	Precision	Recall	Score F1
Normal	0.8845	0.9245	0.9045
Atrial Fibrillation	0.8045	0.8045	0.8045
Other	0.7845	0.7245	0.7545
Noisy	0.6745	0.6445	0.6645

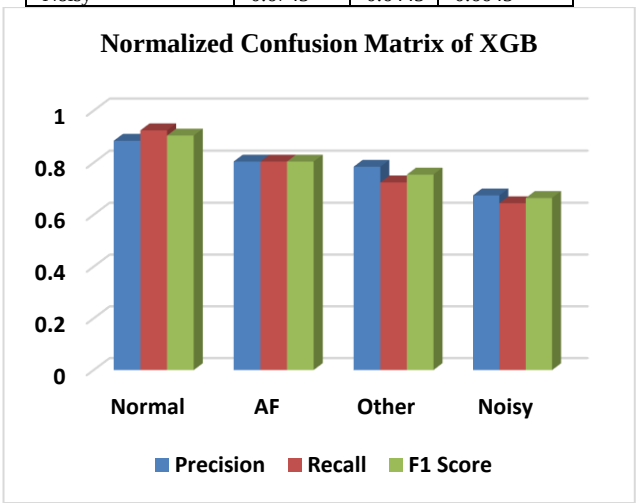

Fig. 3. Normalized confusion matrix of the XGBoost classifier trained on oversampled data

C. Cost-sensitive classification

The MetaCost algorithm proposed in [16] was chosen for this study. Cost-sensitive classification remains a relatively underexplored area. While the significance of the cost matrix for algorithm performance is well-established, as it aims to minimize classification errors, clear guidelines for defining the matrix are lacking, as it varies depending on the specific dataset. In this case, the cost matrix was determined after testing a range of values for the classification errors in the class with the poorest performance (noisy).

TABLE II. METACOST COST MATRIX

	Normal	Atrial Fibrillation	Other	Noisy
Normal	0	1	1	100
Atrial Fibrillation	1	0	1	100
Other	1	1	0	100
Noisy	80	80	80	0

These values were integers between 50 and 200, in increments of 10. A cost of 0 was assigned to the diagonal (correct classifications), and a cost of 1 was used for all other cases. Table 2 presents the resulting cost matrix. Additionally, Table 3 and Figure 4 show the performance of the cost-sensitive XGB model, highlighting a 5% improvement in the F1 score for class 4 compared to the non-cost-sensitive model.

TABLE III. CLASSIFICATION REPORT FOR COST-SENSITIVE XGBOOST CLASSIFIER (METACOST)

Class	Precision	Recall	Score F1
Normal	0.8446	0.9745	0.9045
Atrial Fibrillation	0.7846	0.7245	0.7545
Other	0.8346	0.6245	0.7145
Noisy	0.6846	0.6445	0.6645

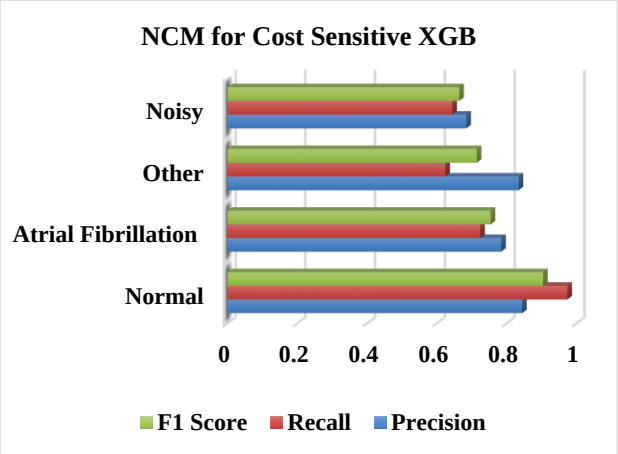

Fig. 4. Normalized confusion matrix for the cost-sensitive XGBoost classifier

In this case, the MetaCost algorithm adjusted 640 labels compared to the original vector. The final costs of the classifier, both with and without MetaCost, were then computed as shown in equation 1, using the non-normalized confusion matrix. As demonstrated in Table 4, MetaCost successfully results in a model with reduced cost and improved average performance.

$$Cost = \sum_{i=1}^{n}\sum_{i=1}^{n}(ConfusionMatrix \odot CostMatrix) \quad (1)$$

TABLE IV. COSTS FINALS ALGORITHM XGBOOST

Algorithm	Cost
XGBoost metacost	3074
XGBoost	3788

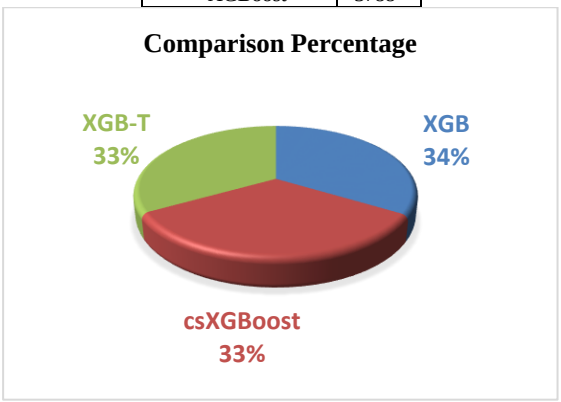

Fig. 5. Comparison of average metrics for treatments against class imbalance

Figure 5 displays the average metric results for the base XGB algorithm, along with the outcomes after applying two data imbalance treatment methods: class oversampling and cost-sensitive classification using the MetaCost algorithm. In conclusion, both methods enhance the model's overall performance, with the oversampling technique yielding more favorable results for precision, recall, and average F1 score, achieving values of 0.77, 0.76, and 0.77, respectively. Figure 5. Comparison of average metrics for class imbalance treatments.

D. Deep Learning Approach

As outlined in the challenge [17] from which the database was derived, the signals were collected using a home ECG from a portable device by AliveCor. Given this, 1-dimensional convolutional neural networks (CNNs) were chosen for this approach due to their proven effectiveness in analyzing time-series and sensor data. Each convolutional network requires a fully connected layer for classification purposes, so the architecture was divided into two parts: a convolutional section and a fully connected section. To determine the optimal architecture, research on similar problems was reviewed, consulting studies [1-7]. After conducting an exhaustive search for hyperparameters, the most suitable architecture was selected. The number of filters ranged from 16 to 128, based on the study in [8] focused on detecting sleep stages from electroencephalography (EEG) signals. Although [8] used a maximum of 64 filters, the search was extended to 128 due to differences in the data (ECG vs. EEG signals) and the fact that the ECG recordings in this study are twice as long (over 60 seconds vs. 30 seconds in the EEG signals of [8]). Filter sizes were tested with values of 3, 5, and 7, following the recommendations in [8] and [6]. The number of convolutional layers varied between 3 and 9. L2 regularization was applied to both the kernels

and the bias. The learning rate and regularization were tested with values of 10^{-4}, 10^{-3}, 10^{-2}, and 10^{-1}. Each convolutional block consisted of a convolutional layer with ReLU activation and a MaxPooling layer with a pool size of 2. For the dense layers, the number of neurons was varied between 128, 64, 32, and 16, using between 2 and 4 layers. The data was split into 80% for training, 10% for validation, and 10% for testing, with the network trained for 250 epochs, as illustrated in Figure 6. The classification results from this architecture are presented in Figure 7.

The proposed deep learning architecture incorporates several layers designed for feature extraction and classification. The model begins with a Masking layer to handle missing values or padding in the input data. This is followed by multiple 1D Convolutional (Conv1D) layers, each equipped with filters, activation functions, and regularization to extract important features from the ECG signals. The first Conv1D layer uses 16 filters with a kernel size of 7, ReLU activation, and l2 regularization of 0.001 to prevent overfitting. After each convolutional layer, a MaxPooling layer with a pool size of 2 reduces the dimensionality while retaining key features.

The convolutional architecture is extended with additional Conv1D layers, starting with 16 filters and progressing to 32, 64, and ultimately 128 filters as the network deepens. These layers consistently use a 7-sized kernel, ReLU activation, and l2(0.001) regularization. MaxPooling layers follow each convolutional block to reduce the feature map size. To improve generalization, a Dropout layer with a rate of 0.5 is added after several later convolutional blocks to randomly disable neurons during training.

After feature extraction, the network progresses to its fully connected (dense) layers. The output from the final Conv1D layer is flattened using a Flatten layer. The fully connected layers begin with a Dense layer consisting of 128 neurons, applying ReLU activation and l2(0.001) regularization. This is followed by a sequence of dense layers with 64 and 32 neurons, each using the same activation function and regularization. Dropout layers with a rate of 0.5 are added between the dense layers to reduce overfitting. Finally, a Dense output layer with 4 neurons and a softmax activation function produces the final class probabilities, which correspond to the four categories: Standard, AF, Other, and Noisy.

Fig. 6. Training and validation accuracy for network architecture

TABLE V. REPORT OF CLASSIFICATION ´N FOR 1D CNN

Class	Accuracy	Recall	Score F1
Normal	0.9046	0.9245	0.9145
Fibrillation headset	0.7846	0.7945	0.7945
Other	0.7946	0.7645	0.7845
Noisy	0.7946	0.7245	0.7545
Average	0.8196	0.8045	0.8145

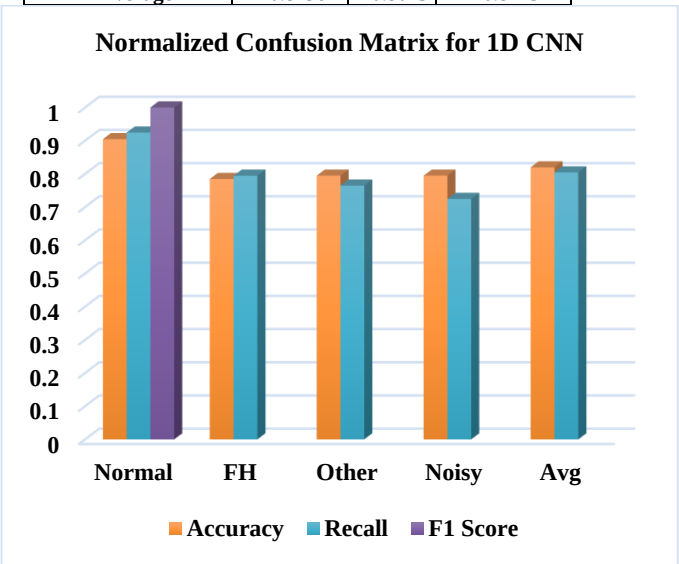

Fig. 7. Normalized confusion matrix for 1D CNN

The model introduced in [7] achieves an average classification F1 score of 78.2%, whereas this work reports an F1 score of 80%, as presented in Table 5. This indicates a potential limitation in [7]'s method of normalizing signal durations to a fixed length. Although this approach is statistically valid, when the signal duration exceeds the fixed length, it is divided into overlapping segments (50% overlap). While this creates more training data, it may also increase dependencies between the segments. The advantages of the approach in this study include, first, maintaining all the original medical data through padding and masking techniques, which helps avoid issues like data dependency and overfitting. Second, a different combination of filter numbers is used (16 to 128 filters, compared to 32 to 512 filters in [7]), resulting in a less computationally demanding model with fewer trainable parameters (720,000 vs. 3.2 million in [7]), thus reducing training time. Third, a different regularization technique (l2 vs. BatchNormalization

in [7]) is applied to both the kernels and bias nodes.

V. CONCLUSION

The study clearly showed that the deep learning approach, particularly the 1D Convolutional Neural Network, surpassed the feature engineering-based XGBoost models in terms of F1 score. This highlights that automated feature extraction using convolutional layers is more effective for the given classification task than manually selecting features. To improve the performance of feature engineering-based models, future research could focus on increasing the number of features, filtering out irrelevant ones, and addressing class imbalance using advanced resampling techniques. Furthermore, a hybrid model combining both methods could be investigated, where the CNN handles feature extraction and the XGBoost model functions as the final classifier. While such an ensemble model would demand more computational power, it could harness the advantages of both approaches and potentially lead to better classification results.

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