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Comparative analysis of feature extraction techniques for imbalanced time-series data

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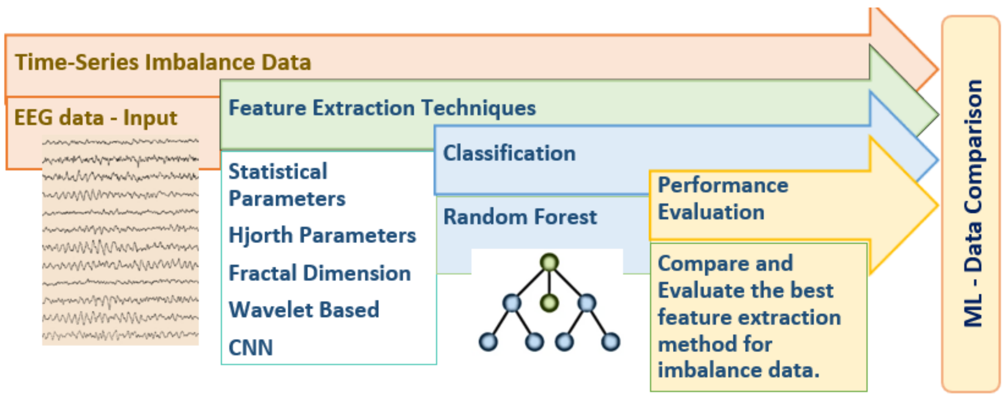
ABSTRACT



Feature extraction significantly enhances the performance of machine learning models. In practical applications, datasets often exhibit an imbalanced distribution. In this paper, the comparative investigation is performed over imbalanced time-series data. For this some best traditional approaches and machine learning approach are selected such as Statistical Parameters, Hjorth Parameters, Fractal Dimension, Wavelet-Based methods, and Convolutional Neural Networks (CNN) respectively. The result was evaluated over DEAP dataset and among all feature extraction methods. Hjorth Parameters and Fractal Dimension follow closely to CNN but less than CNN. CNN achieved the highest accuracy i.e., 82% and it also outperforms other methods.

Keywords: Imbalanced Data, Time-Series Data, Feature Extraction, Convolutional Neural Networks (CNN), Machine Learning.

INTRODUCTION

In today real-world applications, time series forecasting is crucial aspect. One of the common examples of time-series data is electroencephalogram (EEG) that is used to captures electrical activities from brain to understand the neurological functions for diagnosis of various brain activities or disorders. However, raw high-dimensional EEG data are complex in nature and generally contain noise. This will make the analysis and classification challenging. The transformation of the raw EEG data is required for effective feature extraction that contains informative representation [1]. Feature extraction will identify and isolate the relevant patterns, characteristics, and structures from the EEG signals [2]. With these relevant and meaningful features, machine learning is efficient to train and improves the classification performance [3]. There are several techniques of feature extraction can be classified in terms of time-domain, frequency-domain, as well as time-frequency domain methods. Time domain focus on the extraction of EEG signal waveforms such as mean, variance, moment, etc. whereas Frequency-domain methods such as Fourier Transform, Wavelet Transform are used to extract the frequency spectrum [4]. Whereas, time-frequency (TF) domain extracts both time and frequency domains. EEG (Electroencephalography) is widely used for studying cognitive development, socioemotional abilities, and psychopathology from infancy to adulthood due to its low cost, excellent temporal resolution, and robustness against movement and noise. Traditionally, EEG studies have focused on “Event-Related Potentials (ERP)” or “Fourier-based” power analyses. ERPs and Fourier-based power analyses are limited in their ability to capture all information in the EEG signal. ERP analyses assume that there is synchronous neural responses across trials that may lead to the loss of significant activity. Time-frequency (TF) analysis will provide a solution by investigating both time and frequency domain of EEG data and thus help in enhancing the study of cognitive and developmental processes [4]. TF analyses have several advantages over traditional EEG methods that will make them more interpretable and relevant across various disciplines. They are particularly sensitive to developmental changes by differentiating between power and phase information. Additionally, advanced machine learning approaches outperform traditional

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methods for extracting these TF features. Some methods such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks can automatically learn and extract complex features from raw EEG data [5][6]. By accurately classification of these extracted features of EEG data have provided the valuable insights to researchers for better diagnosis, treatment, and understanding of neurological conditions.

This paper primarily contributes a comprehensive comparative analysis of multiple feature extraction techniques applied to time-series EEG data for emotion recognition tasks. Additionally, the paper introduces a CNN-based model tailored to effectively manage class imbalance, a prevalent challenge in biomedical time-series datasets. This specialized model significantly enhances classification accuracy compared to several contemporary classifiers evaluated during benchmarking.

LITERATURE REVIEW

Wang et al. [5] proposed a hybrid model termed as 2D CNN-LSTM for classifying EEG signals for motor imagery (MI) tasks. Feature relationship was established in EEG channels using 2D CNN and then LSTM network was used for training. Xu et al. [6] proposed the feature pattern-based LSTM for observation of imbalance in data and resolve such issues. Hou et al. [7] presented a self-attention-based prediction model to address time-series data. The encoder-decoder architecture of the self-attention mechanism extracts common patterns from time series data for specific time-period to handle imbalance. Schlegl et al. [8] proposed modifications to the shapelet algorithm to consider margin of separation and multivariate dependencies between extracted features. These changes result in more robust and diverse features, improving classification accuracy. Demonstrated the algorithm's applicability to highly imbalanced data using a manufacturing domain dataset. Liu et al. [9] presented the LSTM-based autoencoder for handling imbalance time-series data. This model is integrated with dense weighted small spheres and large margins approach that can balances the imbalance classes. This will enhance the learning process of the classification tasks. Wu et al. [10] reviewed multivariate time series (MTS) data using feature-based classification methods. Yan et al. [11] addressed the challenge of time series classification (TSC) with imbalanced data distributions and proposed a novel oversampling method based on feature extraction for imbalanced TSC. Author extracted representative patterns using shapelets and replaced the information gain with the AUC measure. Author used SMOTE oversampling on the new feature space to generate synthetic data. Salekshahrezaee et al. [12] proposed a method requiring feature extraction before data sampling to enhance classification results. Author used principal component analysis (PCA) and convolutional autoencoder (CAE) for feature extraction and also applied SMOTE for data sampling. Zhu et al. [13] presented the oversampling method that is based on structure-preservation designed for high-dimensional imbalanced time-series data. In this approach, the author used the density-ratio-based shared nearest neighbor clustering algorithm for estimation of minority classes and effective classification. Zhao et al. [14] proposed a novel oversampling method named T-SMOTE to address class imbalance in time-series data. Author also employed a weighted sampling method on both generated and synthetic samples. Fan et al. [15] covered five data augmentation (DA) methods such as repeating minority classes, morphological change, signal segmentation and recombination, dataset-to-dataset transfer, and generative adversarial networks (GAN). These augmentation approaches are used a classification model with a typical convolutional neural network (CNN) architecture to assess the effectiveness of the DA approaches. Gao et al. [16] proposed deep learning model for detection of brain seizure. The model was designed for imbalance data. The model was designed for generative adversarial network (GAN) for detection of seizure-period. Meng et al. [17] proposed WGAN model for performing data augmentation. Fatlawi et al. [18] balanced the minority class with the current window of a data stream. Oviedo et al. [19] Proposes conditional hierarchical forecasting using machine learning to select reconciliation methods for time series hierarchies. Demonstrates improved accuracy, especially at lower hierarchical levels. Iwana et al. [20] provides a taxonomy of data augmentation methods for time series classification, categorized into four families: transformation-based, pattern mixing, generative models, and decomposition. Park et al. [21] introduces a reweighting framework using Local Discrepancy (LD) to address overfitting and data imbalance in time-series forecasting, achieving significant error reduction. Sinha et al. [22] developed a multi-class cardiovascular disease classifier leveraging time-domain augmented features. Compares performance across classifiers and integrates with smart healthcare frameworks. Bousbaa et al. [23] implemented a dynamic DSM methodology using stochastic gradient descent (SGD) for FOREX data prediction, improving accuracy through adaptive sliding windows. Zhang et al [24] proposed a probabilistic autoencoder with multi-scale feature extraction for unsupervised anomaly detection in multivariate time series, achieving superior F1-scores. Espinosa et al. [25] designed a multi-surrogate evolutionary algorithm for feature selection, excelling in regression and classification tasks in air quality and temperature forecasting. Junaid et al. [26] developed an explainable machine learning pipeline for Parkinson’s disease progression prediction, optimizing using Bayesian methods and achieving robust explainability. Zhang et al. [27] introduced TriD-MAE, a pre-trained model for handling missing data in multivariate time series, excelling in classification and prediction tasks. Geng et al. [28] addressed class imbalance in time series classification using cost-sensitive convolutional neural networks (CS-CNN), achieving superior results on public datasets. Huang et al. [29] used nonlinear Granger causality in a neural network model to handle imbalanced multivariate time series, effectively identifying anomalies in flight data. Burhanudin et al. [30] proposed a recurrent neural network for classifying astronomical phenomena, achieving high AUC scores with photometric data and contextual information. Rad et al. [31] developed an anomaly detection and explanation discovery framework using human-interpretable dimensionality reduction (HIDR), improving computational efficiency. Wang et al. [32] combined attention mechanisms with deep learning for time series representation and anomaly detection, demonstrating robustness in fault detection tasks. Michau et al. [33] proposed a fully learnable framework based on fast discrete wavelet transform (FDWT) for unsupervised high-frequency signal analysis, excelling in denoising and representation learning. Zhao et al. [34] introduced a fault diagnosis method using wavelet packet distortion and CNNs to balance datasets, showing improved classification for mechanical systems. Alshamrani et al.[35] designed a deep neural network approach for stress detection using smartwatch data, favoring fully convolutional networks for superior performance.

METHODOLOGY USED

Time series data consists of sequential observations that change over time. These are mapped into a well-defined feature space for use with machine learning algorithms. This involves constructing a feature vector for each time series that captures various linear aspects of the data and nonlinear characteristics. Instead of directly using data points from the time series, it is more efficient to apply characterization methods to extract meaningful features. The resulting feature vectors can be extended with additional univariate attributes and combined with other types of time series data to form a comprehensive design matrix. For machine learning tasks, the significance of these extracted features is crucial to avoid overfitting and ensure the model generalizes well. To address this, parallel feature selection algorithms is used that is based on statistical hypothesis tests that automatically feature characteristics. This approach ensures that only relevant features are used that will enhance the effectiveness and efficiency of the machine learning models.

Feature Extraction Methods for Time-Series Imbalance Data

Statistical Method

Statistical features is used to summarize the distribution and behavior of the time-series data. These features are used for learning the general behavior of the signal. In case of imbalanced time-series data will result in skewness or other statistical anomalies. Therefore, these features are used to identify the outliers. Some of the common features are presented below:

$$\boldsymbol{Mean\ (\mu) = \frac{1}{N}\sum_{i=1}^{N} x_i} \quad \textbf{(1)}$$

$$Standard\ deviation\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \quad (2)$$

$$Skewness\ (sk) = \frac{N}{(N-1)(N-2)}\sum_{i=1}^{N}\left(\frac{(x_i-\mu)}{\sigma}\right)^3 \quad (3)$$

$$Kurtosis\ (Kr) = \frac{N(N+1)}{(N-1)(N-2)(N-3)}\sum_{i=1}^{N}\left(\frac{(x_i-\mu)}{\sigma}\right)^4 - \frac{3(N-1)^2}{(N-2)(N-3)} \quad (4)$$

Where, where x_i is the time-series data point and N is the total number of data points with mean μ. Algorithm for Statistical Parameter Extraction:

- Input: Time-series data $x = [x_1, x_2, \dots, x_N]$.
- Compute μ,σ, sk, Kr using the above equations.
- Output: Feature vector Fstat=[μ,σ, sk, Kr].

Hjorth Parameter based Method

One of the commonly used feature extraction method for time-series data are Hjorth parameters. While in case of imbalanced time-series data, Hjorth parameters shows the variation in data. For example, presence of noise or irregularities in the under-represented data is represented by higher complexity. There are two main Hjorth parameters:

$$\boldsymbol{Mobility\ (Mo) = \sqrt{\frac{var(\dot{x})}{var(x)}}} \quad \textbf{(5)}$$

$$Complexity\ (C) = \frac{Mobility(\dot{x})}{Mobility(x)} \quad (6)$$

Where, $\dot{x}$ is the is the second derivative of the time-series.

Algorithm for Hjorth Parameters:

- Input: Time-series data x.
- First of all variance of the data is evaluated.
- Then, mobility is calculated using the variance of the first derivative.
- Finally, complexity is calculated using the second derivative.
- Output: Feature vector $FHjorth = [Mo, C]$.

Fractal Dimension based Method

The complexity or roughness in time-series data is evaluated using Fractal dimension features. It is used to capture the complexity of data signals that show irregular patterns. In case of imbalanced time-series data, minority class are effectively measured using fractal dimensions. One common method of fractal dimention is the Higuchi Fractal Dimension (HFD). It is evaluated as:

- Create k-subseries of the original signal.
- Calculate the length $L(k)$ of each subseries for different values of k.
- The fractal dimension D is estimated as the slope of the line fitting $log(L(k))\ vs\ log(k)$.

Algorithm for Fractal Dimension (Higuchi's Method):

- Input: Time-series data x.
- For each $k = 1,2, \dots, K$ divide the signal into subseries.
- Then the length $L(k)$ is calculated for each subseries.
- Perform linear regression on $log(L(k))\ and\ log(k)$ to estimate the fractal dimension D.
- Output: Fractal dimension D.

Wavelet-Based Methods

Wavelet Transform provides a time-frequency representation of the signal. Wavelet transforms allow detailed analysis of both local and global signal characteristics. For imbalanced time-series data, this multiresolution analysis can help isolate and highlight differences in behavior between majority and minority class instances, particularly in terms of transient events or noise. The Discrete Wavelet Transform (DWT) decomposes a signal into different frequency components. For a signal x, the DWT is given by:

$$\boldsymbol{x_t = \sum_i \sum_j c_{i,j} \varphi_{i,j}(t)} \quad \textbf{(7)}$$

where $\varphi_{i,j}$ is the wavelet function and $c_{i,j}$ are the wavelet coefficients.

Algorithm for Wavelet-Based Feature Extraction:

- Input: Time-series data x.
- Apply Discrete Wavelet Transform (DWT) to decompose the signal into different levels.
- Extract features such as energy or entropy from the approximation and detail coefficients.
- Output: Feature vector $Fwavelet$.

CNN-Based Methods

In CNN-based feature extraction, time-series data is treated similarly to images. Typically, 1D CNN is used for time-series data: CNN-based feature extraction can automatically detect intricate patterns in the time-series, which are crucial for identifying subtle differences in minority class instances. By learning hierarchical representations, CNNs can capture complex and multi-level features in the data, which is vital when dealing with imbalanced datasets. The convolution operation is:

$$\boldsymbol{f(x) = \sigma(W * x + b)} \quad \textbf{(8)}$$

where W are weights, $*$ is the convolution operator, and σ is the activation function. Pooling layers reduce the size of the feature maps.

Algorithm for CNN-Based Feature Extraction:

- Input: Time-series data x reshaped as a 1D signal.
- Apply 1D convolutional layers to learn local features.
- Use pooling layers to reduce the dimensionality.
- Flatten the final layer and apply a fully connected layer to produce feature vectors.
- Output: CNN feature vector F_{CNN}.

RESULT ANALYSIS

In this study, time-series data is utilized from the DEAP dataset [36], a well-established benchmark in the field of emotion recognition. The dataset comprises recordings from 32 individuals, each exposed to 40 one-minute music video clips intended to provoke emotional reactions. EEG signals captured during these sessions serve as the primary biosignals, inherently exhibiting time-series characteristics. To evaluate the model's effectiveness, several performance metrics are employed:

$$\boldsymbol{Accuracy = \frac{TP + TN}{TP + TN + FP + FN}} \quad \textbf{(9)}$$

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

$$F1\_Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (12)$$

Figure 1 shows the accuracies of different feature extraction techniques for time-series imbalance data. The result shows that Hjorth parameters performed well and achieved an accuracy of 64%. Whereas the Fractal Dimension achieved an accuracy of approx. 62%. Then the statistical parameters achieved and accuracy of 59%. Whereas the Wavelet-Based Methods have achieved an accuracy of 55% which is the least effective among the feature extraction techniques. Therefore, it can be inferred that CNN is the most accurate method for feature extraction in this time-series imbalance data outperforming other techniques like Hjorth Parameters, Fractal Dimension, Statistical Parameters, and Wavelet-Based methods. Traditional feature extraction methods may still be useful but are not as powerful as CNN in handling this type of data.

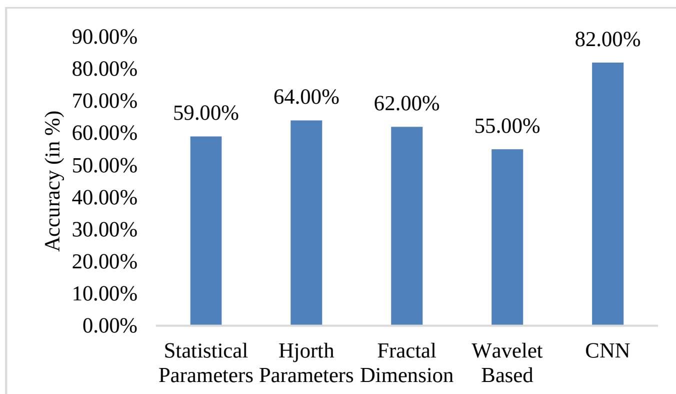

Figure 1. Accuracy Evaluation for Different Feature Extraction for Time-Series Imbalance Data.

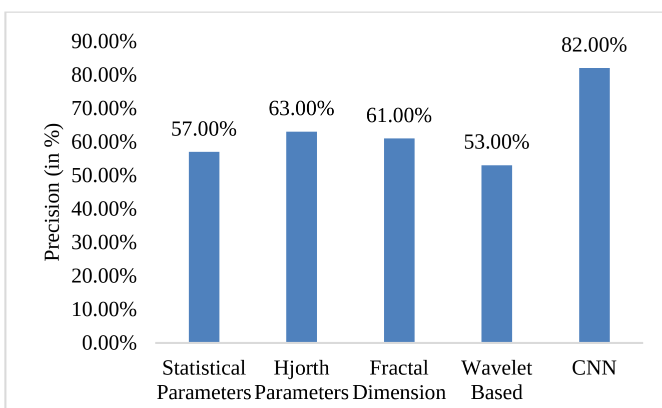

Figure 2. Precision Evaluation for Different Feature Extraction for Time-Series Imbalance Data

The figure 2 shows that the precision values for different feature extraction techniques applied to time-series imbalance data. The results shows that CNN acheived the highest precision of 82%. This implies that CNN is the best feature extraction method for this task when prioritizing precision. Hjorth Parameters and Fractal Dimension achieved an precision of 63% and 61%. Statistical Parameters achieved 57% precision whereas Wavelet-Based Methods performed the lowest precision of 53%.

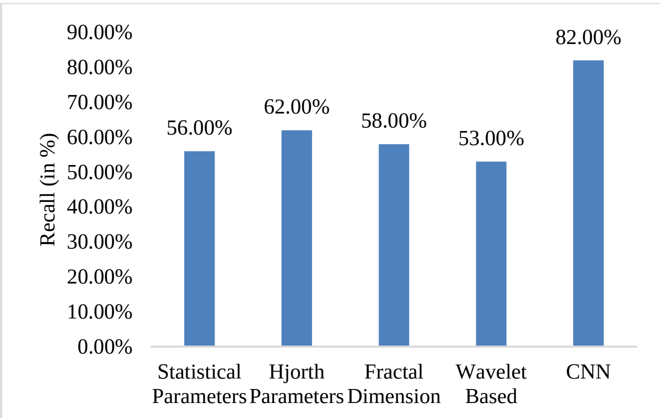

Figure 3. Recall Evaluation for Different Feature Extraction for Time-Series Imbalance Data

The figure 3 illustrates the recall for different feature extraction techniques applied to time-series imbalance data. CNN achieved the highest recall of 82%. Hjorth Parameters shows the second-highest recall of 62%, followed by Fractal Dimension of 58%. Statistical Parameters achieved recall of 56% and Wavelet-Based Methods achieved 53%. Therefore, CNN is the most effective in terms of recall.

The figure 4 presents the F1-Score for different feature extraction techniques applied to time-series imbalance data. The F1-Scores of CNN is 82%. This makes it the most robust method for time-series imbalance data. Hjorth Parameters shows the second-highest F1-Score of 62%. Fractal Dimension achieves a 57% F1-Score. Statistical Parameters has an F1-Score of 56% which is lowest among all.

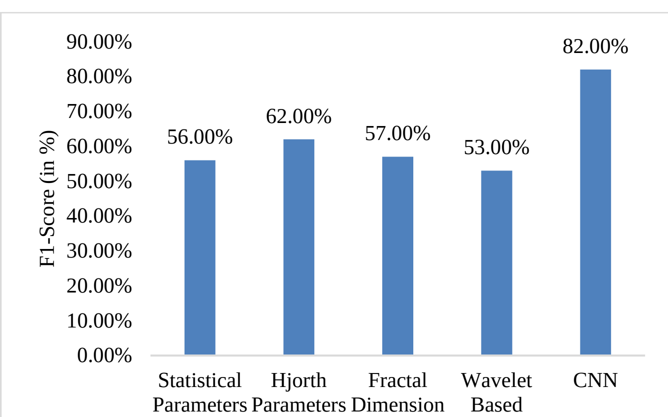

Figure 4. F1-Score Evaluation for Different Feature Extraction for Time-Series Imbalance Data

Table 1 presents a comparison between the CNN approach and several advanced techniques. The methods employ diverse feature extraction approaches, including Hjorth, Wavelet, Differential Entropy, temporal and spatial features, and Genetic Algorithms (GA). The Proposed Adaptive Augmented Technique introduces a novel adaptive augmentation approach, which differentiates it from others. Classification methods used include SVM, GELM, k-NN, RF, and Domain-adaptation.

Table 1 Performance Validation

Classification	Accuracy
SVM [37]	65.92
Domain-adaptation [38]	39
GELM [39]	69.67
RF [40]	64
k-NN [41]	72
CNN	82

The Proposed CNN-based model is well-suited for feature-rich and complex data. None of the compared methods explicitly address data imbalance, which is a critical issue in TS analysis. The suggested approach directly tackles data imbalance, significantly improving its capability to manage practical, real-world situations. The Proposed CNN achieves the highest accuracy of 82%, significantly outperforming all other methods. The lack of imbalance handling in existing methods limits their accuracy. The proposed method's focus on imbalance handling contributes significantly to its superior accuracy.

The paper evaluated various feature extraction techniques for emotion recognition [42][43] using EEG time-series data that is designed to address class imbalance. The CNN-based approach significantly outperformed traditional methods such as Hjorth, Fractal Dimension, Statistical, and Wavelet methods with an accuracy of 82%. Comparative analysis shows that the CNN is better over traditional classifiers like SVM, and GELM due to its explicit handling of imbalance. Future applications could extend beyond emotion recognition into areas such as seizure prediction and sleep-stage classification. Further research may focus on hybrid models, real-time optimization, and explainability for clinical trust and practicality.

Conclusion

This study provides a comprehensive comparison of various feature extraction techniques for handling imbalanced time-series data. For this analysis, traditional approaches such as statistical features, hzorth features, fractal features, and wavelet-features are selected. On the other side CNN model is selected for feature extraction. The results were compared among themselves on EEG signal emotion classification data. There is completely imbalanced data and time-series in nature. On this data each method is applied and results are evaluated for feature extraction. Among all methods, CNN achieves the highest performance making it the most effective method for feature extraction in this context. Traditional methods such as Hjorth Parameters and Fractal Dimension perform moderately well and Wavelet-Based methods and Statistical

Parameters achieved the lowest performance. Therefore, all results shows that CNN is an optimal approach for feature extraction in imbalanced time-series data. Therefore, adoption of deep learning-based feature extraction can significantly enhance the accuracy and reliability of models dealing with such challenging datasets. In future, this work will be extended on hybrid approach for feature extraction over imbalanced data.

Author's Contribution

Harshita Chaurasiya was responsible for the conceptualization, methodology, data analysis, experimental implementation, and original draft preparation of the manuscript. Dr. Anand Kumar Pandey provided supervision, technical guidance, and conducted comprehensive review and revisions to enhance the scientific clarity of the paper.

Conflict of Interest Statement

Authors declare that there is no conflict of interest for this work.

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