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Machine Learning-Based Feature Extraction Techniques for Epileptic Seizure Detection Using EEG Bio-signals

*Ashish Sharma
(Motherhood University, Roorkee, Haridwar, Uttarakhand, India
*Department of Information Technology, College of Engineering and Computer Science, Lebanese French University, Kurdistan Region, Iraq
https://orcid.org/0000-0002-2386-2581, ashish068@gmail.com, *ashish.sharma@lfu.edu.krd)
Vinai K Singh
(Motherhood University, Roorkee, Haridwar, Uttarakhand, India
https://orcid.org/0000-0002-6217-2495, drvinaiksingh@gmail.com)

Abstract: The This paper explores feature extraction algorithms with machine learning strategies to identify epileptic seizures from ElectroEncephaloGram (EEG) signals. Sudden, unpredictable neurological occurrences known as epileptic seizures frequently show up as aberrant electrical activity in the brain. EEG signals offer essential insights into these dynamics, but successful detection requires sophisticated computational methods because of their intrinsic complexity. This study examines feature selection methodologies, which are as follows: correlation-based, information gain, recursive feature elimination, L1 regularization, random forest, principal component analysis, and independent component analysis. This approach enhances the efficacy of diagnostic procedures and facilitates the administration of appropriate therapeutic interventions. These methodologies enable extracting pertinent patterns and features from EEG information. The collected characteristics function as distinctive inputs for machine learning models, facilitating the creation of resilient seizure detection systems. Several machine-learning methods, including Decision Trees (DT), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbor (KNN), and eXtreme Gradient Boost (XGBoost), are utilized to acquire complex patterns from the retrieved information. The presented methodology demonstrates encouraging outcomes regarding sensitivity, specificity, and accuracy for identifying epileptic episodes. This study enhances non-invasive epileptic seizure detection approaches by integrating feature extraction procedures with machine learning techniques. The findings of this study have considerable implications for expediting intervention and tailoring treatment approaches for persons diagnosed with epilepsy, thereby improving their overall quality of life and well-being.
Keywords: Feature extraction methods, Machine learning, Electroencephalogram, Classification algorithms, Epileptic seizure and non-seizure data.

1. Introduction

An epileptic seizure is a chronic neurological and noncommunicable disease with unusual brain electrical activity (Alotaiby et al., 2017; O'Shea et al., 2021), and around the world, more than 60–70 million (Ahmad et al., 2022; Dissanayake et al., 2021) of the population is affected by this disorder. The epileptic patient faces many body control problems due to sudden changes in neurological bio-signal electrical activity (Vidyaratne & Iftekharuddin, 2017). The patients feel dizziness, headache, fainting, loss of mental control, and loss of confidence in working for daily life, including cooking, driving, reading, writing, etc. (Alzami et al., 2018; Samiee et al., 2015). As per the study (Tiwari et al., 2017), the recognition of epileptic seizure patterns by medical practitioners is a challenging and time-consuming task. This study (Parvez & Paul, 2017) shows statistically that some patients have temporal variations in high-frequency oscillation distribution. High-frequency oscillations are becoming a popular electrical seizure biomarker. Hence, opera-tor-independent automated approaches are needed to identify and classify them. So, automated and semi-automated (Tiwari et al., 2017) systems would benefit the medical team to diagnose the patient's disorder and provide timely treatment.

In machine learning and data analysis, feature selection (Dissanayake et al., 2021) is a crucial process that can boost model performance and reduce computing complexity by identifying the most important features or variables. This article shows different methodologies for extracting features from EEG data. It is explained in a literature review section for feature selection processes (Pearce et al., 2013; Zarei & Asl, 2021), which are as follows: correlation-based, information gain, recursive feature elimination, L1 regularization, random forest, principal component analysis, sequential forward se-lection using K-Nearest Neighbors (KNN), and sequential backward selection using KNN. The researchers (Xun et al., 2016) presented a rational Discrete Short Time Fourier Transform (STFT) as an adaptive extension of the conventional STFT. This meth-od was applied to detect epileptic seizures in EEG signals, resulting in a concise representation of the signal in the time-frequency domain. Moreover, the pro-posed technique excellently extracted relevant features from the EEG signals. The authors (Açıkoğlu & Tuncer, 2020) suggested a feature extraction method for EEG data categorization based on picture matching using local binary patterns to identify interest zones, and the proposed method classifies using SVM. The scholars (Ahmad et al., 2022; Gupta et al., 2018; Korshunova et al., 2018) must determine the transition between the interictal and preictal periods to predict the ictal state from EEG. It includes splitting the signal into epochs and extracting global and local features. Two correlated signals' undulated global characteristic is determined by phase correlation. This method can accurately detect motion between pictures or blocks or estimate EEG signal transitions between interictal and preictal/ictal periods. In their study, the researchers (Ozcan & Erturk, 2019) outlined many methodologies that have been devised for the classification of epileptic data. These methodologies encompass wavelet packet analysis, modular energy and modular entropy approaches, non-linear distribution techniques, approximate entropy and sample entropy computations, and the utilization of the greatest Lyapunov exponent and correlation dimension. The article (Ahmad et al., 2022; Billeci et al., 2018) covered epilepsy attack data collection, feature extraction, classification, and post-processing. Although (Stojanović et al., 2020) numerous short-term projections exist, accurately assessing the occurrence of a missed or expected seizure can be a complex task. Two often employed metrics in this context are lead sensitivity, which measures the ability to identify positive cases correctly, and precision, also known as positive predictive value, which quantifies the proportion of correctly identified positive cases out of all the cases identified as positive.

The article follows a structured approach, beginning with an Introduction to outline the context and significance of the research. The background and related work are under Section 2. The Problem statement, Section 3, clearly defines the research problem and objectives. Methodology details the approach to addressing the issue, including data collection, analysis techniques, and modeling methods, in Section 4. Results present the findings obtained from applying the methodology to the dataset, Section 5. Finally, Section 6, the Conclusion, summarizes the key findings, discusses their implications, and suggests directions for future research. This sequential organization ensures a coherent presentation of the research process and its outcomes.

2. Background and Related Work

This research (Xun et al., 2016) introduced an effective and unique feature extraction approach for epileptic seizure detection in EEG recordings. It is explained for rational Discrete STFT (DSTFT) is an adaptive generalization of the classical STFT and also uses rational functions to characterize epileptic seizure patterns in the time-frequency domain. To be as effective as possible, researchers looked at the best number of coefficients and window size to show that the Malmquist–Takenaka rational DSTFT can be used to find seizure patterns in EEGs. The paper (Ahmad et al., 2022) showed that the fundamental purpose is to predict seizures with high accuracy in an automated way successfully. It is explained that for the phase correlation, the cost function of fluctuation and deviation approaches are utilized to extract features, and the least square-SVM classifier and windowing regularization are employed to post-process. In their study, the researchers (Billeci et al., 2018) demonstrated that the adaptive hybrid feature selection-based classifier ensemble (AHFSE) method integrates numerous feature selections in order to acquire the best features that play essential roles in seizure detection and classification performance.

The authors (Pearce et al., 2013) created a feature selection (FS)-based decision support system using neonatal EEG records with and without seizures. With the fewest attributes per channel difference, all FS algorithms performed best. All FS algorithms were tested on each EEG channel with the highest classification performance (98.8%). The suggested procedure employs the discrete wavelet transform (DWT) and orthogonal matching pursuit (OMP) methods to decompose single-channel EEG data into various coefficients. The complexity of

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individual EEG sub-bands is then quantified by non-linear properties such as recurrence quantification analysis, alphabet, correct condition entropies, and others (Li et al., 2020). In order to anticipate when an epileptic seizure would occur, researchers (Wang et al., 2013) examined the complexity of a superset of EEG-based markers typically used to make this distinction. In this classifier-agnostic study, complexity indicators, including the Fisher discriminant ratio and the amount of class overlap in feature space, were employed to determine each feature's discriminant power.

This paper (Ibrahim et al., 2019) proposes a new model for EEG seizure identification using blocked texture features and a representation of time-frequency images in two dimensions (2D-TFI). The model employs STFT to increase the time-frequency representation (TFR) quality by transforming the one-dimensional EEG into a multi-dimensional matrix. In order to ensure the efficacy and practicality of this method, and explore eight actual clinical instances. These encouraging findings highlight the method's potential for further clinical development across various illnesses. Here, researchers (Karabiber Cura et al., 2020) introduce a unique approach to classifying epileptic EEG signals utilizing a multivariate feature classification algorithm based on the union of RF and CNN. The suggested model has perfect classification accuracy, sensitivity, specificity, and precision when extracting numerous characteristics from EEG data. The paper explains DNN model architecture and feature extraction. According to (Yuan et al., 2018), a deep learning neural network (DNN) model can automatically generate features for EEG signal analysis classification tasks. Abstractions can learn complicated operations from input information without manually creating features because the DNN model extracts various features from low to high layers.

3. Problem Statement

This study investigates the effectiveness of feature extraction algorithms combined with machine learning strategies to improve epileptic seizure detection from EEG signals, aiming to enhance diagnostic accuracy and facilitate tailored therapeutic interventions for individuals with epilepsy.

4. Methodology

The methodology used in this article is a six-step process, as shown in Figure 1. Here, the raw signal or EEG bio-signal labelled data, consisting of twenty-three (23) channels in the European Data Format (EDF), was first collected. This data is from CHB-MIT (Deepa B & Ramesh K, 2021). It then converted data to a comma-separated value (CSV) format for each Subject one by one. After this, integrate all of the CSV file data into one file and mention the target values (0 and 1) as per labelled data for the subjects. It represents non-seizure (0) and seizure (1). It is processed and cleaned data with no missing values. Now, it is a continuation process to find the results from this processed dataset of size (5540608, 24).

Different feature extraction techniques apply to the same dataset, as shown in Table 1. These algorithms can pick the relevant features for further processing. This step helps reduce the dimensions of the dataset. As a result, it

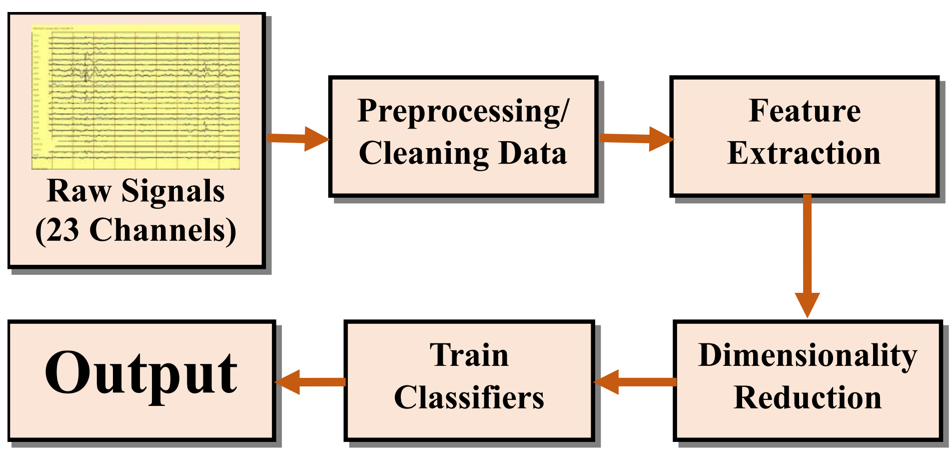

Figure.1. Proposed Methodology for Relevant Feature Extraction

minimizes the computing cost and maximizes the machine learning model's performance to train classifiers. This table describes the various feature selection algorithms and proves the benefits of applying high dimensional data to reduce the features for training the classifiers for machine learning model/s.

Table.1. Feature Extraction Techniques for Selecting Relevant Features from the Dataset

Feature Extraction Technique	Description	Mathematical Expression
Correlation-Based Feature Selection (CBFS)	Correlation-based feature selection filters feature subsets by their correlations with the target variable and each other.	$\textbf{Maximize } J = \sum_{i=1}^{m} s_R(i) - \sum_{i=1}^{m} \sum_{J=I}^{m} s_D(i,j)$ Where **S_R(i)** is the relevance of feature **i** with the target variable and **S_D(i,j)** is the redundancy between features **i** and **j**.
Information Gain Feature Selection (IGFS)	In feature selection, Information Gain (IG) measures how much information a feature provides about the target variable. Decision trees and other classification techniques use it.	$IG(X) = H(Y) - H(Y \mid X)$ $H(Y) = -\sum_{i} P(y_i) \log_2\left(P(y_i)\right)$ $H(Y \mid X) = \sum_{j} P(x_j) H(Y \mid X = x_j)$ Here, Information Gain **IG(X)** of feature **X** with respect to the target variable **Y**, **H(Y)** as the entropy of the target variable **Y**, and **H(Y|X)** as the conditional entropy of **Y** given a feature **X**. Where **P(y_i)** is the probability of class **y_i** in the target variable **Y** and **P(x_j)** is the probability of observing value **x_j** of feature **X**, and **H(Y|X=x_j)** is the entropy of **Y** given feature **X** takes the value **x_j**.
Recursive Feature Elimination (RFE)	It iteratively removes features from the dataset, applies the model to the remaining features, and selects features based on their importance or contribution. The process continues until the selection of the desired number of features. Linear models, tree-based models, or models with built-in feature selection methods that produce feature importance scores benefit from RFE.	**Model = FitModel(X,y)** **ImportanceScores = Φ(Model)** **X=RemoveFeature(X,LeastImportantFeature)** Where **X** is the matrix of features with **n** samples and **m** features, each row represents a sample, and each column represents a feature. **y** as the vector of the target variable, and **Φ** as the feature importance function, which assigns a score to each feature based on its importance.
L1 or Lasso Regularization Feature Selection (LRFS)	It works well for feature selection and model regularization, balancing model complexity with predictive performance. Machine learning uses it to	$\textbf{Loss} = \textbf{Original Loss} + \lambda \sum_{j=1}^{p} \lvert \beta_j \rvert$ Where Original Loss is the loss function without regularization, it means mean-squared error for linear regression and logistic loss for logistic regression.

	penalize the absolute magnitude of model coefficients in linear and logistic regression models. It improves feature selection by encouraging coefficient sparsity, decreasing some coefficients to zero and deleting related features from the model.	**λ** is the regularization parameter, which controls the strength of regularization—higher values of **λ** lead to a more aggressive shrinking of coefficients. **p** is the number of features. $\boldsymbol{\beta_j}$ are the coefficients associated with each feature. $\boldsymbol{\lambda \sum_{j=1}^{p} \lvert\beta_j\rvert}$ is the L1 regularization term. It is added to the original loss function and penalizes large coefficients by shrinking them towards zero.
Random Forest Feature Selection (RFFS)	It facilitates the analysis of training feature significance scores and can be used to select features. Each feature score decides its contribution to training impurity reduction. These scores can identify essential aspects of prospective modelling tasks.	$$\mathbf{FI(X_j) = \frac{Imp(X_j)}{\sum_{i=1}^{m} Imp(X_i)}}$$ Where **X** is the matrix of features with **n** samples and **m** features, each row and column representing a sample and a feature, respectively, and **y** as the vector of the target variable. Here $\mathbf{Imp(X_j)}$ represent the total impurity reduction achieved by splitting on feature $\mathbf{X_j}$. The feature importance score $\mathbf{FI(X_j)}$ for feature $\mathbf{X_j}$ is typically normalized to sum to **1** across all features.
Principal Component Analysis (PCA)	PCA is a sophisticated feature selection method that reduces features to a lower-dimensional space while keeping key information. PCA selects a collection of main components to choose features based on data variance.	$$\sum = \mathbf{Q\Lambda Q^T}$$ Where **X** be the original feature matrix with **n** samples and **m** features. **Q** is an **m×m** matrix whose columns are the eigenvectors of **Σ**. **Λ** is a diagonal matrix containing the eigenvalues of **Σ**. PCA selects the first **k** principal components corresponding to the largest eigenvalues to retain the most significant variance in the data.
Independent Component Analysis (ICA)	Dimensionality reduction method Independent Component Analysis (ICA) splits multidimensional signals into additive, statistically independent components. ICA is commonly utilised for blind source separation and signal processing, but it can choose features.	$$\mathbf{X = AS}$$ Where **X** be the original feature matrix with **n** samples and **m** features. **A** is **n×m** mixing matrix that represents the linear mixing process. **S** is **m×n** matrix of source components. The observed data **X** is represented as a linear mixture of **m** independent source components **S**, here each sample $\mathbf{x_i}$ in **X** is a linear combination of the sources.

5. Results and Discussion

By following the methodology steps in extracting the results to prove this research. After completing the practical in Python programming using Jupyter Notebook on Anaconda Framework. These are the following results in Table 2.

Table.2. Selected Relevant Features by using Feature Extraction Techniques on the Dataset

<table>
<tr><th>Feature Extraction Technique</th><th>Total Number of Channels (or Features)</th><th>Component (k)</th><th>Selected Relevant Features</th></tr>
<tr><td rowspan="3">Correlation-Based Feature Selection (CBFS)</td><td rowspan="10">'# FP1-F7', 'F7-T7', 'T7-P7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3', 'P3-O1', 'FZ-CZ', 'CZ-PZ', 'FP2-F4', 'F4-C4', 'C4-P4', 'P4-O2', 'FP2-F8', 'F8-T8', 'T8-P8-0', 'P8-O2', 'P7-T7', 'T7-FT9', 'FT9-FT10', 'FT10-T8', 'T8-P8-1'</td><td>k = 5</td><td>'T7-P7', 'FZ-CZ', 'T8-P8-0', 'P7-T7', 'T8-P8-1'</td></tr>
<tr><td>k = 10</td><td>'F7-T7', 'C3-P3', 'F4-C4', 'C4-P4', 'FP2-F8', 'T8-P8-0', 'T7-FT9', 'FT9-FT10', 'FT10-T8', 'T8-P8-1'</td></tr>
<tr><td>k =15</td><td>'F7-T7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3', 'FZ-CZ', 'CZ-PZ', 'F4-C4', 'C4-P4', 'FP2-F8', 'T8-P8-0', 'T7-FT9', 'FT9-FT10', 'FT10-T8', 'T8-P8-1'</td></tr>
<tr><td>Information Gain Feature Selection (IGFS)</td><td>k = 5</td><td>'T7-P7', 'P7-T7', 'P7-O1', 'F7-T7', 'F3-C3'</td></tr>
<tr><td>Recursive Feature Elimination (RFE)</td><td>k = 5</td><td>'F7-T7', 'P7-O1', 'F3-C3', 'P7-T7', 'FT9-FT10'</td></tr>
<tr><td>L1 or Lasso Regularization Feature Selection (LRFS)</td><td>NIL</td><td>[ ]</td></tr>
<tr><td>Random Forest Feature Selection (RFFS)</td><td>k = 5</td><td>'P7-T7', 'T7-P7', 'F7-T7', 'P7-O1', 'FT9-FT10'</td></tr>
<tr><td>Principal Component Analysis (PCA)</td><td>k = 10</td><td>'PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8', 'PC9', 'PC10', 'result'</td></tr>
<tr><td>Independent Component Analysis (ICA)</td><td>k = 10</td><td>'IC1', 'IC2', 'IC3', 'IC4', 'IC5', 'IC6', 'IC7', 'IC8', 'IC9', 'IC10'</td></tr>
</table>

The table outlines various feature extraction techniques, the total number of channels or features, the number of components (k) selected, and the chosen features for each method. In CBFS, different values of k result in selecting specific channels deemed most relevant for seizure prediction. IGFS prioritizes features based on information gain, with selected channels like T7-P7 and P7-O1 considered crucial. RFE identifies important features iteratively, with prominent channels such as F7-T7 and P7-O1 emerging as significant. L1 or LRFS, Random Forest (RF) feature selection, and PCA each offer distinct approaches to feature selection, with selected features tailored to optimize predictive performance. ICA identifies independent components contributing to the overall data, highlighting components like IC1 and IC2 as influential. Each technique offers unique insights into feature importance, aiding in developing effective seizure prediction models tailored to EEG data.

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It is describing the important features from twenty-three channels to further processing steps. It is shown in Figure 2. In predicting seizures from EEG channels, it's crucial to visualize the essential features along with their corresponding importance scores to gain insights into their predictive power. Among the provided EEG channels, T7-P7 emerges as the most crucial feature, with a score of 59.66, suggesting its pivotal role in seizure prediction.

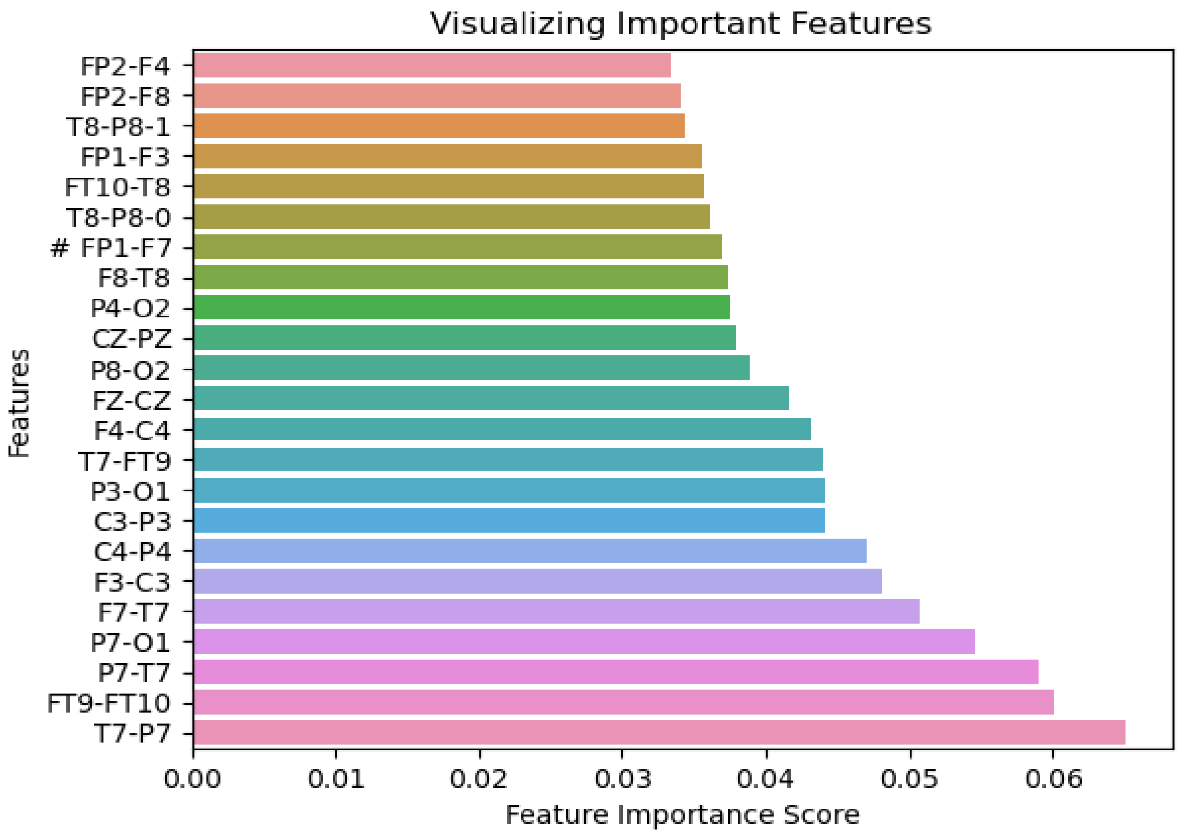

Figure.2. Visualization of Important Features with each Feature Importance Score

The closely followed channels are FT9-FT10 and P7-T7, with high importance scores of 58.55 and 58.49, respectively, highlighting their significant contributions to the predictive model. Additionally, features such as P7-O1, F3-C3, and F7-T7 exhibit moderately high importance scores ranging from 53.56 to 56.43, indicating their relevance in seizure prediction. While C4-P4 and C3-P3 have comparatively lower importance scores of 46.81 and 44.77, they still offer valuable insights into seizure prediction. Visualizing these essential features and their respective importance scores provides a comprehensive understanding of the relative importance of EEG channels

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in predicting seizures, enabling researchers and clinicians to prioritize specific channels for further investigation and intervention strategies.

This research focuses on the relationship between various features. It also explains the impact of their correlation for further studies in predicting epileptic seizures from EEG data. See Figure 3, checking correlation in the data is a crucial step in data analysis as it helps to identify relationships between different variables. Examining the correlation coefficients can filter out unnecessary columns, as lower correlation values indicate lower attribute importance.

When the correlation coefficient is close to +1, it indicates a strong positive correlation between the variables. It means that the variables tend to vary in the same direction simultaneously, i.e., as one variable increases, the other variable also tends to increase. Conversely, when the correlation coefficient is close to -1, it signifies a robust negative correlation between the variables. In this scenario, the variables tend to vary in the opposite direction simultaneously, i.e., as one variable increases, the other variable tends to decrease. A correlation coefficient close

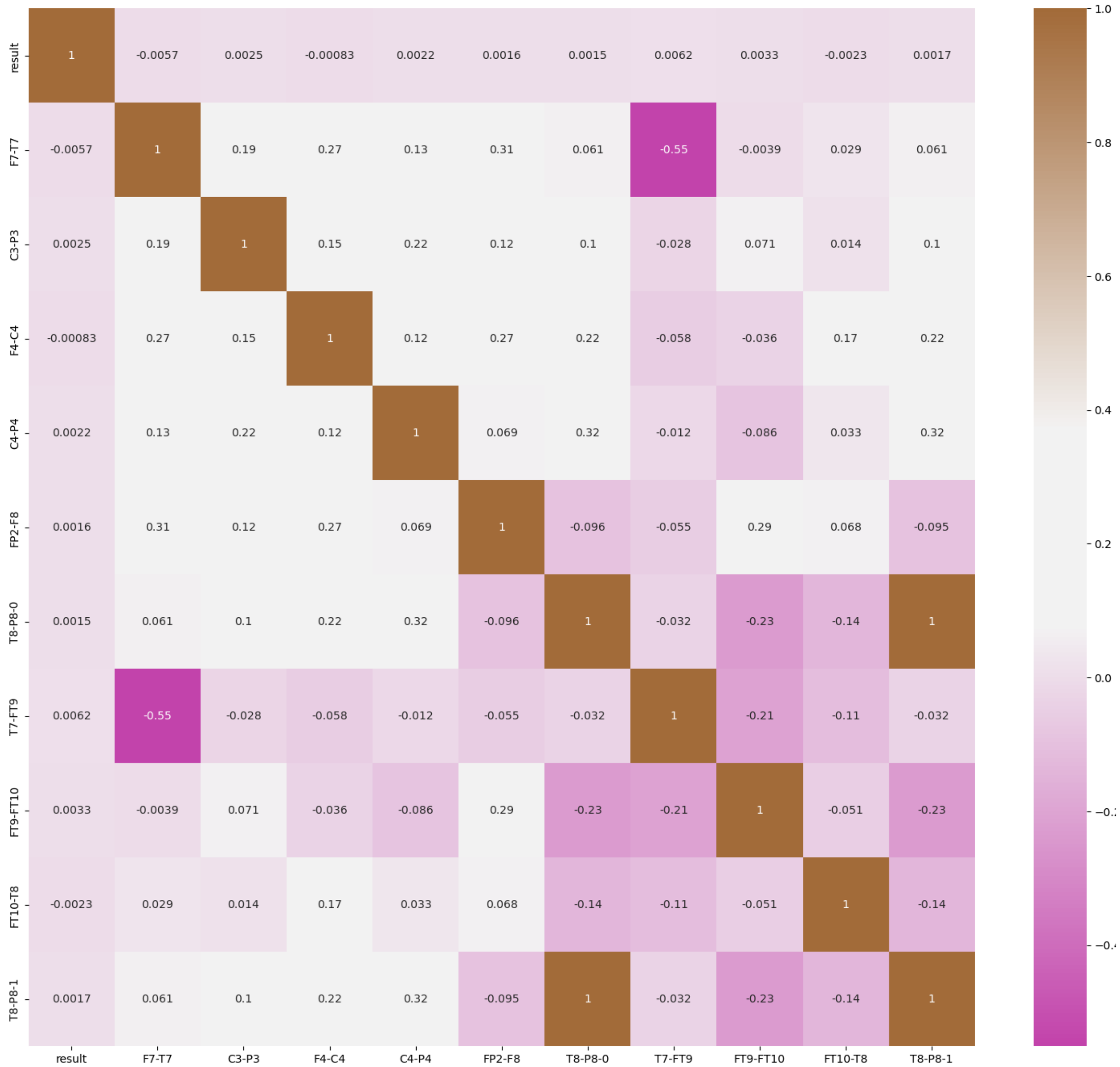

Figure.3. Representation of Correlated Features

to 0 indicates little to no linear relationship between the variables. It suggests that the variables are not correlated and do not exhibit a consistent pattern of variation together.

Table.3. Performance Metric by using Machine Learning Techniques on Selected Relevant Features from the Dataset

Machine Learning Techniques	Accuracy	Precision	Recall	F1-Score	MCC
DT	0.656928	0.651683	0.656256	0.653961	0.313821
RF	0.754061	0.807816	0.658879	0.725786	0.515636
NB	0.659340	0.791453	0.421422	0.549992	0.355454
KNN	0.757772	0.790543	0.693346	0.738761	0.518617
XGBoost	0.716184	0.760047	0.621740	0.683972	0.438228

From Table 3, it is an empirical performance analysis of various machine learning models evaluation after selecting ten features (F7-T7, C3-P3, F4-C4, C4-P4, FP2-F8, T8-P8-0, T7-FT9, FT9-FT10, FT10-T8, T8-P8-1) from an initial set of twenty-three features. Decision Tree (DT) achieved an accuracy of approximately 65.69% with precision, recall, and F1-score around 65.17%, 65.63%, and 65.40%, respectively, along with an MCC of 31.38%. Random Forest (RF) outperformed DT, achieving an accuracy of approximately 75.41% with higher precision (80.78%), recall (65.89%), and F1-score (72.58%), as well as a higher MCC of 51.56%. Naive Bayes (NB) demonstrated an accuracy of approximately 65.93% with precision and F1-score around 79.15% and 55.00%, respectively, while its recall and MCC were comparatively lower at 42.14% and 35.55%. K-Nearest Neighbors (KNN) showed promising results with an accuracy of approximately 75.78% and relatively high precision (79.05%) and recall (69.33%), achieving an F1-score of 73.88% and an MCC of 51.86%. XGBoost achieved an accuracy of approximately 71.62% with precision, recall, and F1-score of roughly 76.00%, 62.17%, and 68.40%, respectively, and an MCC of 43.82%. Overall, Random Forest and K-Nearest Neighbors demonstrated the highest performance among the models, followed by XGBoost, Decision Tree, and Naive Bayes, underscoring the importance of feature selection in enhancing model performance and efficiency.

6. Conclusion

In conclusion, the table illustrates various feature extraction techniques employed in predicting seizures from EEG channels. Each method, including Correlation-Based Feature Selection (CBFS), Information Gain Feature Selection (IGFS), Recursive Feature Elimination (RFE), L1 or Lasso Regularization Feature Selection (LRFS), Random Forest (RF) feature selection, Principal Component Analysis (PCA), and Independent Component Analysis (ICA), offers unique insights into the importance of features extracted from the initial set of twenty-three channels. Notably, different values of k in CBFS, information gain in IGFS, and iterative selection in RFE highlight specific channels crucial for seizure prediction, such as T7-P7 and P7-O1. Visualization of these essential features, as demonstrated in Figure 2 and their importance scores, underscores the pivotal role of channels like T7-P7 and FT9-FT10 in predictive modeling. Furthermore, moderately high importance scores of channels like P7-O1, F3-C3, and F7-T7 emphasize their relevance in seizure prediction. Even channels with comparatively lower importance scores, such as C4-P4 and C3-P3, contribute valuable insights. This research delves into the intricate relationship between various features and elucidates the profound impact of their correlation in predicting epileptic seizures from EEG data. As illustrated in Figure 3, the examination of correlation coefficients emerges as a crucial step in data analysis, identifying relationships between different variables and facilitating the filtration of unnecessary columns. A correlation coefficient close to +1 signifies a strong positive correlation, while a value near -1 indicates a robust negative correlation between variables. Conversely, a correlation coefficient close to 0 suggests little to no linear relationship.

Furthermore, empirical performance analysis, as presented in Table 3, highlights the efficacy of various machine learning models after selecting essential features from an initial set of twenty-three. Notably, Random Forest and K-Nearest Neighbors exhibit superior performance, emphasizing the significance of feature selection in optimizing model performance. Overall, visualizing essential features and their importance scores facilitates a comprehensive understanding of the importance of EEG channels in seizure prediction, guiding researchers and clinicians in prioritizing specific channels for further investigation and intervention strategies. These findings underscore the importance of meticulously examining feature relationships and selecting pertinent features for accurate seizure prediction, ultimately enhancing the efficiency and efficacy of predictive modeling in EEG data analysis.

References

[1] Açıkoğlu, M., & Tuncer, S. A. (2020). Incorporating feature selection methods into a machine learning-based neonatal seizure diagnosis. *Medical Hypotheses*, *135*, 109464. https://doi.org/10.1016/j.mehy.2019.109464

[2] Ahmad, I., Wang, X., Zhu, M., Wang, C., Pi, Y., Khan, J. A., Khan, S., Samuel, O. W., Chen, S., & Li, G. (2022). EEG-Based Epileptic Seizure Detection via Machine/Deep Learning Approaches: A Systematic Review. *Computational Intelligence and Neuroscience*, *2022*, 1–20. https://doi.org/10.1155/2022/6486570

[3] Alotaiby, T. N., Alshebeili, S. A., Alotaibi, F. M., & Alrshoud, S. R. (2017). Epileptic Seizure Prediction Using CSP and LDA for Scalp EEG Signals. *Computational Intelligence and Neuroscience*, *2017*, 1–11. https://doi.org/10.1155/2017/1240323

[4] Dr. B. Sasikala "Role of Artificial Intelligence in Marketing Strategies and Performance" Migration LettersVolume: 21, No: S4 (2024), pp. 1589-1599, SSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

[5] Alzami, F., Tang, J., Yu, Z., Wu, S., Chen, C. L. P., You, J., & Zhang, J. (2018). Adaptive Hybrid Feature Selection-Based Classifier Ensemble for Epileptic Seizure Classification. *IEEE Access*, *6*, 29132–29145. https://doi.org/10.1109/ACCESS.2018.2838559

[6] Billeci, L., Marino, D., Insana, L., Vatti, G., & Varanini, M. (2018). Patient-specific seizure prediction based on heart rate variability and recurrence quantification analysis. *PLOS ONE*, *13*(9), e0204339. https://doi.org/10.1371/journal.pone.0204339

[7] Dr.S. Umamaheswari, "Role of Artificial Intelligence in The Banking Sector" Journal of Survey in Fisheries Sciences 10(4S) 2841-2849, 2023.

[8] Deepa B, & Ramesh K. (2021). *Preprocessed CHB-MIT Scalp EEG Database*. https://doi.org/10.21227/awcw-mn88

[9] Dissanayake, T., Fernando, T., Denman, S., Sridharan, S., & Fookes, C. (2021). Deep Learning for Patient-Independent Epileptic Seizure Prediction Using Scalp EEG Signals. *IEEE Sensors Journal*, *21*(7), 9377–9388. https://doi.org/10.1109/JSEN.2021.3057076

[10] Gupta, A., Singh, P., & Karlekar, M. (2018). A Novel Signal Modeling Approach for Classification of Seizure and Seizure-Free EEG Signals. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *26*(5), 925–935. https://doi.org/10.1109/TNSRE.2018.2818123

[11] Barinderjit Singh "Artificial Intelligence in Agriculture" Journal of Survey in Fisheries Sciences, 10(3S) 6601-6611, 2023.

[12] Ibrahim, F., Abd-Elateif El-Gindy, S., El-Dolil, S. M., El-Fishawy, A. S., El-Rabaie, E.-S. M., Dessouky, M. I., Eldokany, I. M., Alotaiby, T. N., Alshebeili, S. A., & Abd El-Samie, F. E. (2019). A statistical framework for EEG channel selection and seizure prediction on mobile. *International Journal of Speech Technology*, *22*(1), 191–203. https://doi.org/10.1007/s10772-018-09565-7

[13] Karabiber Cura, O., Kocaaslan Atli, S., Türe, H. S., & Akan, A. (2020). Epileptic seizure classifications using empirical mode decomposition and its derivative. *BioMedical Engineering OnLine*, *19*(1), 10. https://doi.org/10.1186/s12938-020-0754-y

[14] Korshunova, I., Kindermans, P.-J., Degrave, J., Verhoeven, T., Brinkmann, B. H., & Dambre, J. (2018). Towards Improved Design and Evaluation of Epileptic Seizure Predictors. *IEEE Transactions on Biomedical Engineering*, *65*(3), 502–510. https://doi.org/10.1109/TBME.2017.2700086

[15] Li, Y., Liu, Y., Cui, W.-G., Guo, Y.-Z., Huang, H., & Hu, Z.-Y. (2020). Epileptic Seizure Detection in EEG Signals Using a Unified Temporal-Spectral Squeeze-and-Excitation Network. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *28*(4), 782–794. https://doi.org/10.1109/TNSRE.2020.2973434

[16] O'Shea, A., Ahmed, R., Lightbody, G., Pavlidis, E., Lloyd, R., Pisani, F., Marnane, W., Mathieson, S., Boylan, G., & Temko, A. (2021). Deep Learning for EEG Seizure Detection in Preterm Infants. *International Journal of Neural Systems*, *31*(08), 2150008. https://doi.org/10.1142/S0129065721500088

[17] Ozcan, A. R., & Erturk, S. (2019). Seizure Prediction in Scalp EEG Using 3D Convolutional Neural Networks With an Image-Based Approach. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(11), 2284–2293. https://doi.org/10.1109/TNSRE.2019.2943707

[18] Parvez, M. Z., & Paul, M. (2017). Seizure Prediction Using Undulated Global and Local Features. *IEEE Transactions on Biomedical Engineering*, *64*(1), 208–217. https://doi.org/10.1109/TBME.2016.2553131

[19] Pearce, A., Wulsin, D., Blanco, J. A., Krieger, A., Litt, B., & Stacey, W. C. (2013). Temporal changes of neocortical high-frequency oscillations in epilepsy. *Journal of Neurophysiology*, *110*(5), 1167–1179. https://doi.org/10.1152/jn.01009.2012

[20] Samiee, K., Kovacs, P., & Gabbouj, M. (2015). Epileptic Seizure Classification of EEG Time-Series Using Rational Discrete Short-Time Fourier Transform. *IEEE Transactions on Biomedical Engineering*, *62*(2), 541–552. https://doi.org/10.1109/TBME.2014.2360101

[21] Stojanović, O., Kuhlmann, L., & Pipa, G. (2020). Predicting epileptic seizures using nonnegative matrix factorization. *PLOS ONE*, *15*(2), e0228025. https://doi.org/10.1371/journal.pone.0228025

[22] Tiwari, A. K., Pachori, R. B., Kanhangad, V., & Panigrahi, B. K. (2017). Automated Diagnosis of Epilepsy Using Key-Point-Based Local Binary Pattern of EEG Signals. *IEEE Journal of Biomedical and Health Informatics*, *21*(4), 888–896. https://doi.org/10.1109/JBHI.2016.2589971

[23] Vidyaratne, L. S., & Iftekharuddin, K. M. (2017). Real-Time Epileptic Seizure Detection Using EEG. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(11), 2146–2156. https://doi.org/10.1109/TNSRE.2017.2697920

[24] Wang, S., Chaovalitwongse, W. A., & Wong, S. (2013). Online Seizure Prediction Using an Adaptive Learning Approach. *IEEE Transactions on Knowledge and Data Engineering*, *25*(12), 2854–2866. https://doi.org/10.1109/TKDE.2013.151

[25] Xun, G., Jia, X., & Zhang, A. (2016). Detecting epileptic seizures with electroencephalogram via a context-learning model. *BMC Medical Informatics and Decision Making*, *16*(S2), 70. https://doi.org/10.1186/s12911-016-0310-7

[26] Yuan, Q., Zhou, W., Xu, F., Leng, Y., & Wei, D. (2018). Epileptic EEG Identification via LBP Operators on Wavelet Coefficients. *International Journal of Neural Systems*, *28*(08), 1850010. https://doi.org/10.1142/S0129065718500107

[27] Zarei, A., & Asl, B. M. (2021). Automatic seizure detection using orthogonal matching pursuit, discrete wavelet transform, and entropy based features of EEG signals. *Computers in Biology and Medicine*, *131*, 104250. https://doi.org/10.1016/j.compbiomed.2021.104250