ENSEMBLE MACHINE LEARNING MODEL FOR DETECTION OF AMYOTROPHIC LATERAL SCLEROSIS

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***Abstract*—A type of motor neuron disease is called amyotrophic lateral sclerosis. Its symptoms include breathing difficulties and a lack of control over the arms and legs, and it is detected by the nerve cells in the nervous system and the spine and early medical intervention, better disease management, research advancements, clinical trial enrolment, using the Ensemble Machine Learning has significant advantages for ALS patients. It emphasizes the potential for machine learning techniques to assist in the early diagnosis of challenging disorders like ALS, which would be advantageous for the healthcare sector. Early detection of Amyotrophic Lateral Sclerosis enhancing the health and quality of life of a patient and helping patients and caregivers overcome the difficulties brought on by this terrible illness are all priorities. Although, using other Supervised learning which gives results about detection of neuron disorder, it is presumed that Ensemble Machine Learning provides better conclusions.**

***Index Terms*—ALS Clinical Trails Database, Machine Learning Algorithms, Pooled Resource Open Access, Graphical User Interface, Motor Neuron Disease Diagnosis.**

I. Introduction

ALS is a progressive and fatal neurodegenerative disorder affecting nerve cells in the brain and spinal cord. Patients with ALS experience muscle weakness, impairing their ability to speak, swallow, and breathe, ultimately leading to paralysis and respiratory failure. Ensemble Machine learning algorithms have shown remarkable capabilities in analyzing complex datasets, making them valuable tools in medical diagnosis. These algorithms can identify patterns and correlations within large datasets, aiding in the early and accurate detection of diseases, including neuro-degenerative disorders like ALS. The primary goal of this project is to develop an ALS detection system using Ensemble Machine Learning algorithms. By leveraging these machine learning techniques, the project aims to create a reliable and precise tool capable of analyzing diverse patient data, including clinical observations and genetic markers. The successful implementation of this project not only enhances the quality of life for ALS patients but also contributes to advancements in the field of neurodegenerative disease research and healthcare technology.

II. Literature Review

Milosz Jamrozy [1] utilizes diffusion tensor imaging (DTI) acquired from common 1.5-Tesla MRI scanners to enhance the diagnosis of ALS. This approach involves evaluating five machine learning classifiers based on apparent diffusion coefficient and fractional anisotropy DTI parameters, specifically focusing on manually selected regions of interest (ROIs) at the level of the brain pyramids in 47 ALS patients and 55 healthy subjects. The effectiveness of each classifier is assessed using confusion matrices and ROC curves. The radial kernel support vector machine (SVM) classifier achieves 77% accuracy in distinguishing between ALS patients and healthy individuals. The study supports the use of SVM for identifying radiological features indicative of ALS. Advantages include the cost-effectiveness of the measurement tool when paired with the highly accurate SVM classifier. However, a notable disadvantage is the absence of investigation into ALS diagnosis using the Random Forest classifier, which may potentially yield superior predictive results compared to other machine learning classifiers.

Ernesto Iadanza [2] thoroughly investigates the application of machine learning techniques in the context of ALS. The study involved collecting diverse ALS-related datasets from medical records, the general population, and academic organizations. Data preparation processes, including cleaning, feature extraction, and selection, were rigorously applied to ensure data readiness for analysis. Various machine learning models were explored, and their efficacy was evaluated

using cross-validation techniques and standard metrics. The study emphasized interpretability and explainability of models to uncover predictive characteristics and underlying disease mechanisms. Additionally, critical evaluation of the limitations of applying machine learning in ALS research was conducted, highlighting potential directions for future advancements in the field. Advantages include providing critical insights into pitfalls and guiding the development of more robust ALS prediction models. However, a notable disadvantage is the dependence on the quality and availability of ALS-related datasets, which could potentially limit the generalizability of findings.

Kyriaki Founta [3] involved generating induced pluripotent stem cells (iPSCs) from skin fibroblasts of 15 sporadic ALS patients and 15 healthy controls without genetic alterations. These iPSCs were differentiated into spinal motor neurons (MNs), which were then immunostained using Neurofilament H as a neuronal marker. Confocal microscopy was used to capture images of the stained MNs, which were subsequently classified as healthy or ALS using a convolutional neural network (CNN). The CNN was trained on a dataset of 130 images (65 healthy and 65 ALS) and evaluated on a held out test set of 30 images (15 healthy and 15 ALS), achieving a 0.97 area under the curve (AUC) for ALS MN image classification with 97% accuracy. This indicates that the CNN model can effectively predict ALS using MN images. The study authors suggest that future research could further validate ALS diagnosis and potentially offer preventative care using their deep learning model. Advantages include being the first to use deep learning for ALS prediction using iPSC-derived MN images. However, a notable disadvantage is the cost and time required to generate iPSC-derived MN images for analysis.

A. Bakiya [4] focuses on three types of data—thoracic, lumbar metabolomic, and microbiome—to investigate gene expression in motor neurons of genetically modified mice, distinguishing between those with fast versus slow progression of ALS. The study employed accuracy, F1 score, and recall metrics to evaluate performance. Using machine learning techniques and murine neuron models, researchers identified ALS progression indicators related to immune response characteristics. This approach paves the way for discovering biomarkers specific to different subgroups of ALS patients. Advantages include analyzing 64 mice affected or unaffected by ALS using machine learning techniques. However, a limitation is the study's focus on discriminating the progression rate of ALS-linked gene mutations rather than distinguishing between different ALS mutations.

Aicha Mokdad[5] involves the creation and validation of an objective machine learning-based metric to assess disease severity in ALS patients. The study utilized a large dataset comprising clinical evaluations, biomarkers, and neuroimaging data from ALS patients at various disease stages. Data pre-processing included standardization, feature extraction, and handling missing values. Various machine learning algorithms such as Gradient Boosting, Random Forest, and SVM were employed to develop prediction models. Cross-validation ensured model robustness, with evaluation metrics including accuracy, specificity, and sensitivity rigorously validated. Feature significance techniques were applied to visualize key factors influencing disease severity, enhancing model interpretability. This approach aims to provide a reliable tool for objectively monitoring ALS progression, potentially aiding clinical decision-making. Advantages include offering a data-driven measure for ALS severity assessment. However, challenges in model interpretability may hinder precise understanding of factors driving disease severity predictions.

KwangHoon An[6] introduces an algorithm called Statistically Equivalent Signature (SES) for feature selection based on causality, identifying a subset of genes most causally related to ALS while considering complex gene interactions. This approach was evaluated using two publicly available ALS RNA-seq datasets and achieved high classification accuracy for both, demonstrating its efficacy in identifying disease-associated genes and training accurate machine learning classifiers for ALS. Overall, the SES methodology shows promise for enhancing ALS prognosis, diagnosis, and treatment by identifying relevant disease-associated genes. Advantages include its ability to develop precise machine learning classifiers for ALS, even with limited sample sizes. However, a limitation is that only sporadic ALS patients without known ALS-related genetic mutations were included, necessitating further validation in a broader patient cohort, including familial ALS cases.

Turner MR[7] proposes automatic classification for diagnosing ALS based on gait time series data. The study preprocesses gait data and extracts features such as fluctuation magnitude and dynamics using coefficients of variation. Five machine learning classifiers were evaluated for their accuracy in distinguishing ALS patients from healthy individuals, with KNN and SVM achieving the highest accuracy of 89.7%, sensitivity of 76.9%, and specificity of 100%. Advantages include higher accuracy when using data from the left foot alone, focusing on metrics derived from fluctuation magnitude and dynamics. A limitation noted was that combining data from both feet did not significantly improve accuracy, suggesting potential asymmetry in gait characteristics between ALS patients and healthy individuals.

Faghri F[8] focuses on using intelligible speech patterns to create a unique technique for early ALS diagnosis. This approach relies on a substantial dataset of speech recordings from both ALS patients and healthy individuals. Data preprocessing techniques such as noise reduction, feature extraction, and data augmentation were employed to enhance model resilience. CNNs were selected as the primary architecture for identifying and classifying speech features. The study implemented rigorous data partitioning, cross-validation, and performance evaluation using metrics like accuracy, sensitivity, and specificity. Interpretability analyses were also conducted to visualize the CNN's learned features, elucidating distinctive speech traits crucial for early ALS detection. This research aims to offer an effective, non-invasive tool for diagnosing

ALS early, potentially improving patient outcomes and treatment options. Advantages include providing a non-invasive and potentially cost-effective method for early ALS detection through speech analysis. However, a limitation lies in its dependency on the quality and quantity of voice data, which could restrict its applicability in certain contexts.

Maj E, Jamrozy M[9], researchers collected multiomics data encompassing transcriptome, epigenome, and genome sequence data from hiPSC-derived ALS motor neurons and healthy controls. They employed various machine learning algorithms to analyze this data and uncover novel transcriptional and mutational signatures associated with ALS. Validation of their discoveries was conducted using independent datasets and clinical samples, revealing a consistent transcriptional signature in ALS motor neurons characterized by elevated expression of genes linked to stress response and synaptic dysfunction, independent of the disease's genetic cause. Advantages of the study include robust validation using diverse datasets and clinical samples, enhancing the generalizability and clinical relevance of their findings. However, a notable limitation is the absence of immediate development of new diagnostic tools or treatments for ALS, although the insights gained could pave the way for future advancements in these areas.

In methodology [11], researchers developed a diagnostic framework for detecting ALS based on the evaluation of EMG data. The study involved collecting diverse and representative EMG datasets from ALS patients and healthy individuals. Signal preprocessing techniques were applied to enhance signal quality by reducing noise. Time-domain and frequency-domain features were extracted from the EMG signals to gather relevant data. Feature selection methods were employed to identify the most discriminative characteristics, thereby improving model effectiveness and interpretability. Machine learning models such as SVM and Random Forest were utilized for ALS categorization, and their performance was evaluated using metrics including accuracy, sensitivity, specificity, and ROC-AUC. This methodology aims to provide an efficient and non-invasive tool for early ALS detection, potentially improving patient care and treatment options. Advantages include the use of feature selection to enhance diagnostic precision and interpretability of the model. However, challenges such as variability in patient participation during data collection and signal variability may impact the effectiveness of EMG-based diagnosis in certain cases.

Maj E, Jamrozy M [12], researchers developed a classification approach for EMG data from ALS patients, myopathy sufferers, and healthy controls using a deep neural network (DNN). The DNN model was trained on a subset of the most informative features selected using the bat algorithm. The study reported high accuracy in classifying EMG data, achieving 98.6% overall accuracy and distinguishing between myopathy and ALS with 99.3% accuracy. The DNN model outperformed traditional machine learning methods like SVM and Random Forests in this context. This research represents a promising advancement towards a more accurate method for EMG data classification, potentially enhancing the management and diagnosis of ALS and myopathy patients. However, further validation and assessment in clinical settings are necessary. Advantages of the methodology include the use of feature selection via the bat algorithm, which enhances model precision and reduces overfitting risks. A limitation noted is the absence of comparison with other machine learning algorithms specifically tailored for EMG classification, which could provide additional insights into comparative performance.

TABLE I
COMPARISON WORK OF THE LITERATURE REVIEW

Ref No	Dataset	Accuracy	Algorithm	Reliability
Milosz Jamrozy, et al. [1]	47 ALS and 55 Healthy people	77%	SVM, KNN, DT, Navie Bayes	Low
Ernesto Iadanza, et al. [2]	Gene Expression Dataset	79%	SVM, LDR, KNN, DT	Medium
Kyriaki Founta, et al.[3]	Gene Targeting Data	83.2%	SES	High
A. Bakiya, et al.[4]	100 people of myopathy suffers	93.3%	Bat Algorithm, Neural Networks	High
Aicha Mokdad, et al.[5]	8 ALS and 30 Healthy	87.4%	SVM, RF	Medium
KwangHoon An, et al.[6]	Speech data of ALS patients	72.5%	CNN	Low
Turner MR, et al.[7]	Sizable dataset of speech recordings from ALS patients	75.4%	CNN	Low
Faghri F,et al. [8]	pertinent data	82.7%	KNN,SVM	High
Fukushima K, et al.[9]	Collection of EMG data from both ALS patients and healthy people	95.7%	RF,SVM	High
Margarida Antunes,et al.[11]	Data from ALS patients, myopathy sufferers	98.6%	Bat Algorithm,DNN	High
Maj E, Jamrozy M, et al.[12]	Collected multiomics data	84.9%	hiPSC	Medium

III. Proposed Methodology

The suggested method is broken down into four stages: 1. The collection of a ALS Dataset. 2. Preprocessing of the dataset. 3. Feature selection and classification 4. Training and

testing of images with different Ensemble Machine Learning algorithms.

A. Data Preparation

The combined dataset of hand grip strength and muscle strength for ALS detection involves a number of steps in data preparation. First, gather the raw data from 293 cases, checking to ensure that each entry is complete and accurate. Next, normalize the data to standardize the range of values across different attributes. Next, take care of any missing values by removing or imputation. Divide the dataset into training and testing sets while maintaining an appropriate ratio to allow for a thorough model evaluation.

B. Feature Selection and Classification

The process of selecting features for ALS diagnosis include minimizing dimensionality, improving model performance, and locating important characteristics from data sources such as speech and motor activities. In order to increase the precision and resilience using the ensemble model which combines Different Machine Learning classifiers of ALS detection.

C. Proposed Approach

Pre-processing data on hand grip and muscular strength from both healthy persons and ALS patients is part of the system architecture for ALS diagnosis utilizing Ensemble Machine Learning in order to manage missing values, outliers, and noise. When necessary, encode categorical variables and standardize features. To find pertinent characteristics for ALS identification, combine statistical testing, domain knowledge, and Random Forest feature importance analysis. To guarantee models are tested on untested data, divide the dataset between training and testing subsets. Then, compare the results to see if the model is classified as ALS or not.

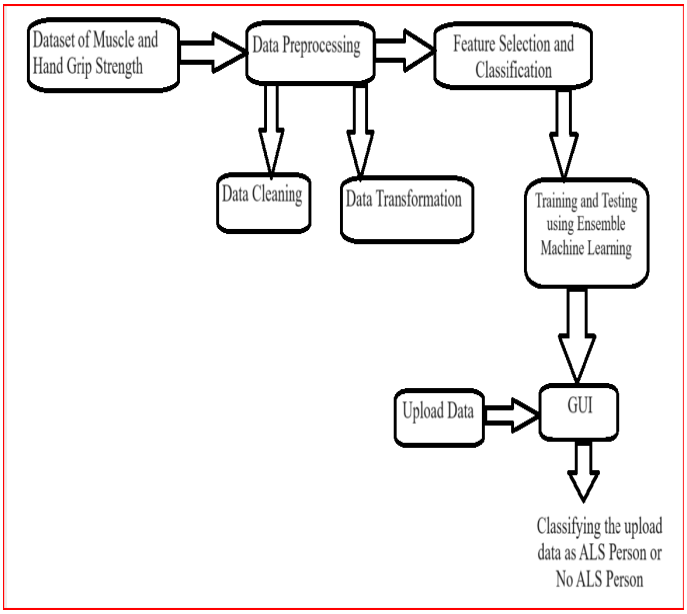

Fig. 1. Proposed Methodology of ALS Detection

D. Process Flow Diagram

A process or system is represented visually in a process flow diagram. It illustrates the movement of materials, information, and activities through the many stages of a process using a variety of shapes, symbols, and arrows. The suggested system executes the model's algorithms, lets the user enter input for each designated location, and makes predictions using the result. The pre-processed data is output as ALS or not ALS

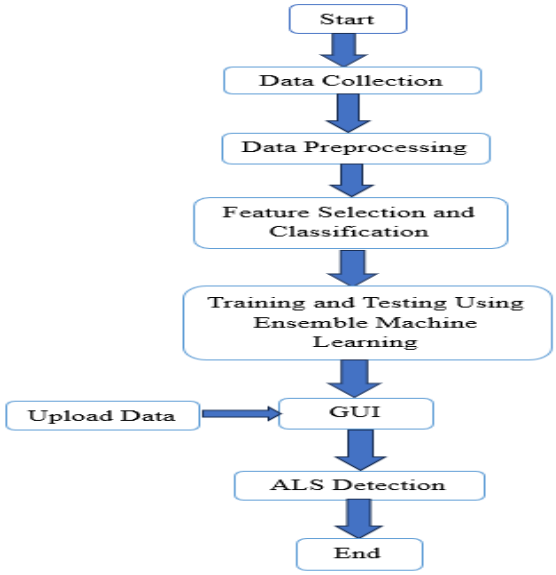

Fig. 2. Process Flow of ALS Detection

E. Training & Testing of Ensemble Machine Learning Models

We tested several combinations of multiple classifiers for training and assessing photos using various Ensemble Machine Learning techniques. The K-Nearest Neighbour (KNN) and Random Forest Forest ensemble continuously produced the best results with 96& accuracy., offering the highest accuracy in image classification tasks, after we evaluated the models based on accuracy.

IV. Results & Disscusion

A. Comparative Model Analysis

The examination of several ensemble machine learning models emphasizes how crucial it is to select the best classifier combinations in order to increase accuracy. With the greatest accuracy rate of 96% among the studied models, the KNN + Random Forest ensemble was shown to be the most successful. This combo makes use of Random Forest's resilience against overfitting and KNN's capacity to handle local data patterns. Even with their strong performances, other models fell short of the KNN + Random Forest ensemble's level of performance. Therefore, the key to getting the greatest results in picture classification problems is choosing the optimum ensemble strategy.

TABLE II
ENSEMBLE MACHINE LEARNING MODEL ANALYSIS

Ref No	Ensemble Model Analysis	Accuracy Rate
[3.1]	KNN + Random Forest	96%
[3.2]	SVM + KNN	83%
[3.3]	SVM + Random Forest	85%
[3.4]	KNN + Decision Trees	78%
[3.5]	Naive Bayes + Random Forest	74%

The accuracy rates and performance analyses of many ensemble machine learning models are shown in the following table. Outperforming other combinations, the KNN and Random Forest ensemble obtained the greatest accuracy of 96%. The accuracy rates of the SVM + KNN and SVM + Random Forest models were 83% and 85%, respectively. On the other hand, the accuracy rates of the KNN + Decision Trees and Naive Bayes + Random Forest ensembles were 78% and 74%, respectively, lower.

B. Outputs

This section discusses the outcomes produced by the suggested ALS detection system. The results highlight the effectiveness of the system's implementation in accurately identifying ALS. The user interface, illustrated in Figure 3, provides a clear and interactive way to input data and view prediction results.

Fig. 3. Output of GUI for ALS Detection

The GUI output for ALS detection is shown in Figure 3. The interface shows important components such input data fields, processing indications, and the final classification output in a visual format, providing an overview of the outcomes produced by the ALS detection system.The result image for the identification of ALS is described in below Figure 4.

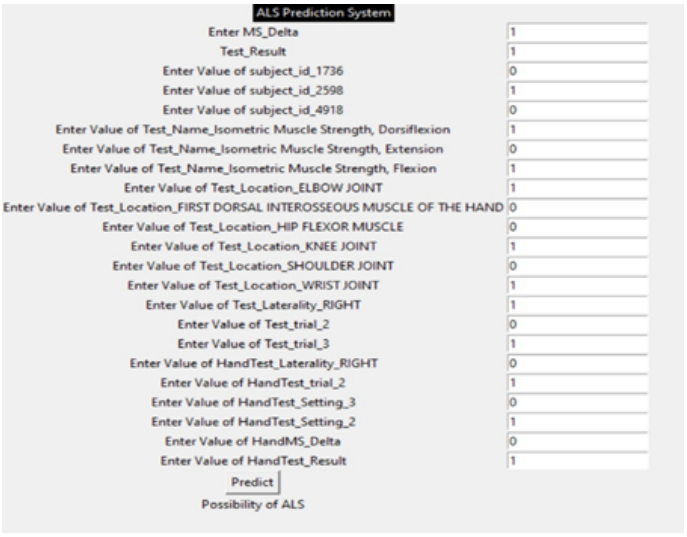

Fig. 4. Output of ALS Detection

The above Figure 4 shows the image you provided is a form for an ALS prediction system. Users input data about various factors related to ALS, and the system predicts the possibility of the disease.

C. Confusion Matrix

Confusion matrix is a table that shows how well a classification model performs by contrasting expected and actual labels. The Figure 6 presents the confusion matrix to identify the ALS.

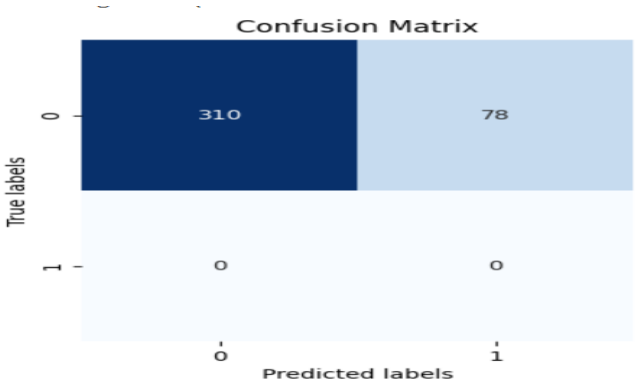

Fig. 5. Confusion Matrix of ALS Recognition

Above Figure 6 displays a table layout that enables one to assess an algorithm's accuracy in terms of right and incorrect

predictions. The matrix shows how many true positive (310), false negative (1), and false positive (78) predictions the algorithm produced.

D. Performance Metrics

Performance metrics are used to evaluate the effectiveness and calibre of a ensemble machine learning model. These metrics provide numerical data that assesses the model's performance on a dataset. Accuracy, Precision score, Recall, f1-score, and AUC-ROC are common measures. The below Figure 7 acknowledges the comparison of performance indicators.

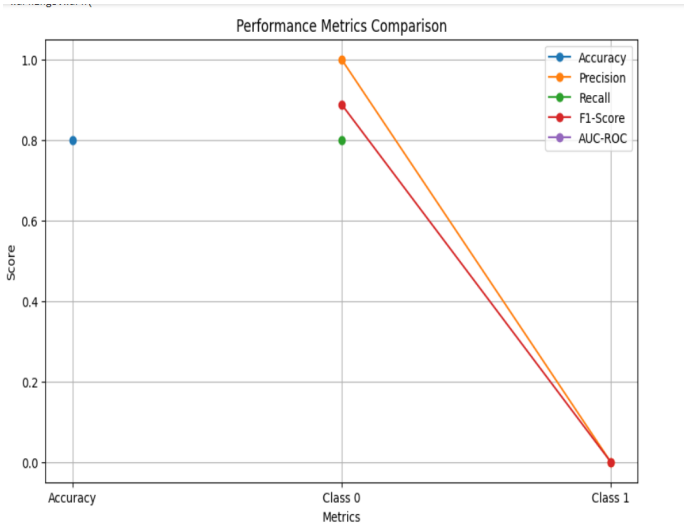

Fig. 6. Comparison of Performance Metrics

The Figure 9 shows the comparative investigation of a ensemble classification model that distinguishes ALS. Specificity detects non-cases, whereas sensitivity assesses the model's accuracy in identifying instances. Recall and precision are balanced in the F1 score, which has an overall accuracy of 96%. The discriminative power of the model is further assessed by the AUC-ROC curve, which guarantees specificity to avoid false alarms and sensitivity to the existence of disease.

V. CONCLUSION AND FUTURE WORK

As a result, our work effectively combined the Random Forest and K-Nearest Neighbours (KNN) algorithms to create an ensemble model for the identification of Amyotrophic Lateral Sclerosis (ALS). The ensemble technique shows improved accuracy and resilience in ALS detection by utilising the variety in predictions from both Random Forest and KNN. We were able to produce a more accurate and reliable classification by combining the strengths of the two models, highlighting the promise of ensemble approaches in medical diagnosis. Although this research represents a substantial advancement, there is still opportunity for greater investigation, including the incorporation of new machine learning algorithms and the use of various data sources, opening the door for future development of more sophisticated and precise ALS diagnostic tools.

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