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Machine Learning Technology Used to Assist the Detection of Alzheimer's Disease

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Abstract: Alzheimer's disease (AD) represents a neurological condition that impairs daily functioning and causes progressive cognitive impairment. AD must be identified as early as possible in order to allow for effective treatment and better patient outcomes. Additionally, in the last few decades, machine learning has become a potent tool for aiding AD identification. So, using machine learning (ML), this research offers a modified probabilistic neural-adaptive naive Bayes (MPN-NB) for diagnosing AD. The suggested strategy combines both NB and probabilistic neural network (PNN) techniques. This study uses the ADNI dataset to analyze the suggested MPN-NB approach. In terms of multiple metrics, including accuracy, sensitivity, Precision, specificity, and f-measure, the performance of the suggested method is assessed. It is clear that our suggested method performs better in detecting AD than the other ones that are already in use.

Keywords: *Alzheimer's disease, detection, machine learning (ML), modified probabilistic neural-adaptive naive Bayes (MPN-NB)*

1. Introduction

Machine learning techniques are transforming medical care, particularly in the fields of sickness detection and treatment. One area where machine learning has demonstrated enormous potential is in the early identification and diagnosis of Countless individuals with the progressive brain disorder known as AD affects people all over the globe. Memory loss, reasoning problems, and behavioral abnormalities are some of the cognitive functions that gradually deteriorate with AD. Early illness detection is essential for prompt management and better patient outcomes [1]. The symptoms of AD might overlap with those of other types of dementia and cognitive decline, making an accurate diagnosis of the condition difficult. Machine learning algorithms have evolved into powerful tools for analyzing huge amounts of data and identifying trends that are difficult for humans to recognize. Machine learning techniques may be used in the context of AD to analyze multiple sorts of data, such as Neuroimaging scans, genetic data, and cognitive tests, to help with early detection and precise diagnosis [2].

To better comprehend the anatomical and operational modification in the brain caused by AD, brain imaging data obtained by techniques like "positron emission tomography (PET)" and "magnetic resonance imaging (MRI)" can be used. Machine learning algorithms may be trained to examine these scans and find certain biomarkers or disease-related patterns. Machine learning algorithms are able to produce a probability or risk score indicating the possibility of Alzheimer's by comparing an individual's scan to a vast database of scans from both healthy persons and those who have the condition [3]. Machine learning can use genetic data in addition to neuroimaging data to help identify AD. An elevated risk of the illness has been linked to specific genetic variants. Genetic data may be analyzed by machine learning algorithms to find significant genetic markers or patterns that could increase an individual's risk of getting AD rises. The accuracy of the models used to forecast AD can be increased by combining this information with data from other sources. Additionally, machine learning models may be built using behavioral and cognitive evaluation data to identify minor changes in cognition that could be signs of AD in its early stages [4]. These models can spot aberrations from typical cognitive function and raise a red signal for further investigation by looking for trends in test results, response times, and other cognitive measures. There is a lot of promise for machine learning technology to be used in the detection and diagnosis of AD. Machine learning algorithms can assist in early diagnosis, resulting in more timely treatments and improved patient outcomes, by examining a variety of datasets and spotting complicated

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patterns. Machine learning is predicted to become more and more important in the battle against AD as this field of study develops [5].

In this study, a modified probabilistic neural-adaptive naive Bayes (MPN-NB) method is presented for the diagnosis of AD. The recommended approach integrates naive Bayes (NB) and probabilistic neural network (PNN) methods. The recommended MPN-NB strategy is examined in this study using the ADNI dataset.

The remainder of the paper is divided into subsequent parts. Part 3 contains the method explained. Part 4 contains the result. Part 5 discusses the conclusions.

2. Related Works

In the study [6], a meta-analysis was done to assess the utilization of new biomarkers and artificial intelligence in the identification of AD. The researchers sought publications and studies that examined the use of machine learning as well as new biomarkers in detecting AD in the Central Register of the Cochrane Library of Controlled Trials, the Cochrane Library of Systematically Relevant Reviews, and PubMed. In order to assist families in better understanding how their patients' diseases evolve so that they may take proactive steps to slow the disease's progression, this research introduced a new approach that employs the spectrogram characteristics generated from speech data to diagnose AD [7]. The study [8] proposed a unique machine learning-based method for diagnosing and tracking AD-like disorders. Deep learning is utilized to evaluate magnetic resonance imaging (MRI) scans in order to identify AD-like problems. Next, a lifestyle monitor system is employed that tracks the subject's daily activities with the use of inertial measurement devices that are put on their own bodies. In order to diagnose AD in its early stages, the study [9] used machine learning algorithms to interpret data collected by neuroimaging technology. The study [10] discussed the findings and analyses related to the identification of dementia using several machine-learning models. The method was developed using data from the "Open Access Series of Imaging Studies (OASIS)."

The study [11]created a system that can automatically identify the illness in uncommon sagittal magnetic resonance imaging (MRI). These data sets included sagittal MRIs from ADNI and OASIS. In addition to outlining the use of deep learning techniques in AD detection, the study [12] discussed ad-related biomarkers and feature extraction techniques, examined and summarized AD detection models, and assessed their applicability. Magnetic resonance imaging (MRI) data is used to classify AD using a deep convolutional neural network (DCNN). Memory loss and the deterioration of cognitive skills are the early signs of Alzheimer's disease (AD), an irreversible neurological brain illness [13]. The study [14] focused on AD, Parkinson's disease, and schizophrenia while comparing and evaluating the efficacy of existing deep learning (DL)-based algorithms to diagnose neurological disorders using MRI images collected through different approaches, such as functional and basic MRI. The study [15] was to develop a Computer-Aided-Brain-Diagnosis (CABD) system that can determine whether an AD brain scan shows indications. The approach classifies data from MRI imaging using a range of extraction of feature methods. In hospitals, the non-invasive MRI technique is routinely used to check for abnormalities in cognition.

3. Methodology

3.1. Dataset

The "Alzheimer's Disease Neuroimaging Initiative (ADNI)" provided the information for this paper. The dataset comprises 110 AD, 105 MCI, and 51 NC patients, with 44–50 picture samples for each person [18]. The Horizontal Scanning Center has gathered data on 110 AD individuals. A total of 9540 photos were utilized for training the network, while 4193 images were utilized for evaluating it. Rescale operations are used to add data to photographs.

3.2. Modified Probabilistic Neural Network (MPNN)

The MPNN invented by Specht is a one-pass learning technique that may be applied to memory association, categorization, and projection. Despite sacrificing the benefits of Specht's PNN, Zaknich introduces an altered PNN that may be utilized for nonlinear time series research. Utilizing the connections between Gaussian Radial Basis Functions and the PNN architecture allows for this. Similar to PNN, MPNN training relies on recollection and only needs a single pass. Input matrices used for training are stored in the network's centers throughout training. The metrics of the intended results are allocated to these centers. The kernel formula is used for assessing the "closeness" of an input vector for testing to each of the centers throughout categorization. The probable outcome is one connected to the center that is closest to the vector of inputs.

There are significant parallels between the fundamental MPNN and “Generic Regression Neural Network (GRNN)” approaches. A commonly used GRNN formula is shown in Equation 1.

$$\hat{z}(y) = \frac{\sum_{j=1}^{MW} z_j \exp\frac{-\left(y-y_j\right)^U\left(y-y_j\right)}{2\sigma^2}}{\sum_{\mathrm{j=1}}^{\mathrm{MW}} \exp\frac{-\left(y-y_j\right)^U\left(y-y_j\right)}{2\sigma^2}} \qquad (1)$$

where y_j represents the training vectors for the group in the contribution space; σ represents the single softening or training variable set as part of network education; z_j

represents the scalar output associated with y_j; and MW represents the total number of training vectors.

Each learning information pair is included in the design of the GRNN in equation (1). A suitable generic model to utilize for the MPNN is if it can be assumed that there is a matching scalar output z_j for each local area in the middle vector's representation of the source field d_j into which it maps.

$$\hat{z}(y) = \frac{\sum_{j=1}^{MW} y_j z_j \exp\frac{-(y-d_j)^U(y-d_j)}{2\sigma^2}}{\sum_{j=1}^{MW} y_j \exp\frac{-(y-d_j)^U(y-d_j)}{2\sigma^2}} \quad (2)$$

The class's average or middle vector in the input field; σ a single smoothing or learning parameter selected during network education; z_j production associated with (quantized); y_j no of input learning vectors linked to center d_j; M number of distinct centers in the MPNN structure. The figure 1 shows the structure of MPNN.

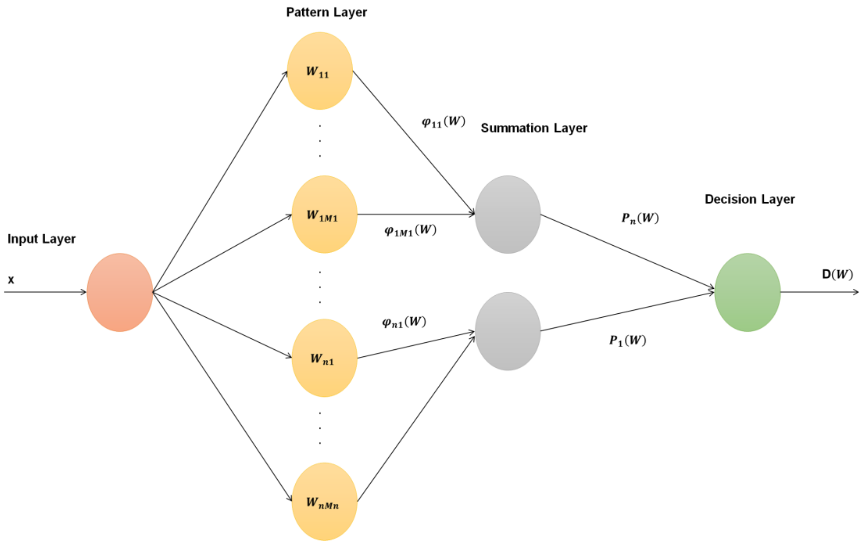

Fig 1: Structure of MPNN

3.3. Naive Bayes (NB)

Predictive classifiers known as naive Bayes forecasters use the Bayes theorem while operating on erroneous (naive) claims regarding the independence of the attributes. A Naive Bayesian framework is particularly useful for detecting cardiac individuals in the field of medical science since it is easy to build and does not require time-consuming iterative variable estimations. Although straightforward, the Naive Bayesian classifier consistently outperforms more advanced classification techniques, which explains why it works exceptionally well and is frequently employed.

From $P(d), P(y)$, and $Q(y|d)$, the posterior probability, $Q(d|y)$, may be calculated using the Bayes theorem. The Naive Bayes classifier presumes that a predictor value has an impact on classification accuracy. The outcomes of the remaining forecasters are irrelevant to (y) on a specific class (d). Class-dependent independence is the term for it.

$$Q(d|y) = \frac{Q(y|d)Q(d)}{Q(y)} \quad (3)$$

$$Q(d|y) = Q(y_1|d) \times Q(y_2|d) \times \ldots \times Q(y_n|d) \times Q(d) \quad (4)$$

The posterior probability of a class (target) given a predictor (attribute) is denoted by$Q(d|y)$.

The previous likelihood of a class is represented by (d).

The likelihood, or$Q(y|d)$, determines how likely a prediction is for a certain class.

The previous likelihood of the predictor is $Q\ (y)$.

Given that it is raining, the chance that the train will arrive on time, where D and Y are two events. The concept of probability is used by these Naive Bayes classifiers to determine the categorization of an unknown (unclassified) occurrence that is most likely. When given categorical information, the algorithm works well, but when given numerical data as part of the training set, it works badly.

3.4. Modified probabilistic neural-adaptive naive Bayes (MPN-NB)

Step 1: Utilize the Naive Bayes technique to compute class-wise attribute stats.

Step 2: Store the statistical data for every category, such as the mean and variance.

Step 3: Use the Naive Bayes classifier to determine the likelihood of each class for a certain test case.

Step 4: Based on the probabilities, order the classes.

Step 5: Choose the top-k courses based on likelihood.

Step 6: To calculate the likelihood of each chosen class, use the PNN method.

Step 7: Choose the class with the best likelihood of getting the test case.

The PNN-NB technique is capable of efficiently handling extremely dimensional data and producing reliable classification forecasts because it combines the Naive Bayes classifier for feature likelihood estimation and the PNN for probability calculation.

4. Result

Implementation of the proposed model uses the Keras library and a Tensorflow backend. The studies are carried out on a Dell Intel Corei9 laptop with 16 GB of RAM. The model is trained using a 16 GB memory NVIDIA Ge Force 540 M GPU.

Accuracy (%), Precision (%), Sensitivity (%), Specificity (%), and f-measure (%) are analyzed. The existing methods are KSVM-DT [16] and PCA-SVR [17], compared with the proposed method (MPN-NB).

A measure of an outcome or result's correctness or accuracy is called accuracy. It is frequently applied when assessing the effectiveness of a model, system, or process by contrasting the projected or accomplished results with the actual or intended results.

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \times 100 \qquad (5)$$

Figure 2 shows the accuracy of the suggested and accepted methods. While KSVM-DT and PCA-SVR only obtain 87.6% and 89.1% accuracy, respectively, the proposed approach MPN-NB receives 98.5% accuracy. MPN-NB proposed method is more accurate than traditional methods.

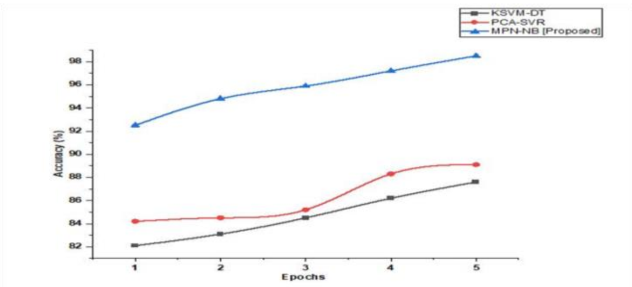

Fig 2: Accuracy

In general, the term "sensitivity" describes the capacity to notice or take in minute fluctuations, changes, or signals. It is a way to gauge how open or closed a system, organism, or person is to a given stimulus or input. Figure 3 illustrates the sensitivity of the suggested and accepted methods. The recommended method, MPN-NB, achieves an accuracy of 96.7%, while KSVM-DT and PCA-SVR only achieve a sensitivity of 88.65% and 90.21%, respectively. MPN-NB procedures provide a higher sensitivity % as compared to traditional methods.

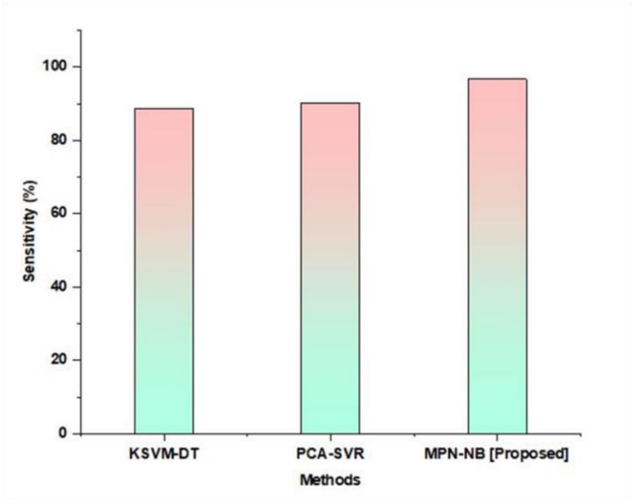

Fig 3: Sensitivity

A model or system's accuracy in properly identifying positive instances or true positives is measured statistically as "precision." It is frequently applied in statistics and machine learning, particularly for binary classification issues.

$$Precision = \frac{TP}{TP + FP} \qquad (6)$$

Figure 4 shows the Precision for the suggested and common techniques. The methods mentioned While KSVM-DT and PCA-SVR only receive 89.52% and 91.81% precision, respectively; MPN-NB receives 96.52% precision. The precise % of MPN-NB techniques is higher than that of conventional methods.

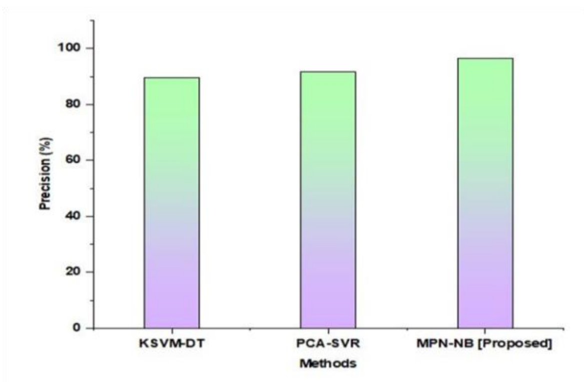

Fig 4: Precision

The term "specificity" describes the property or state of being particular, accurate, or precise. It refers to how clearly something is defined, concentrated, or restricted to a certain set of qualities, traits, or circumstances. Figure 5 depicts the specificity of the suggested and standard methods. While KSVM-DT and PCA-SVR achieve 87.23 and 91.52 percent specificity, respectively, MPN-NB achieves 97.23 percent. MPN-NB methods offer a greater specificity rate than older techniques.

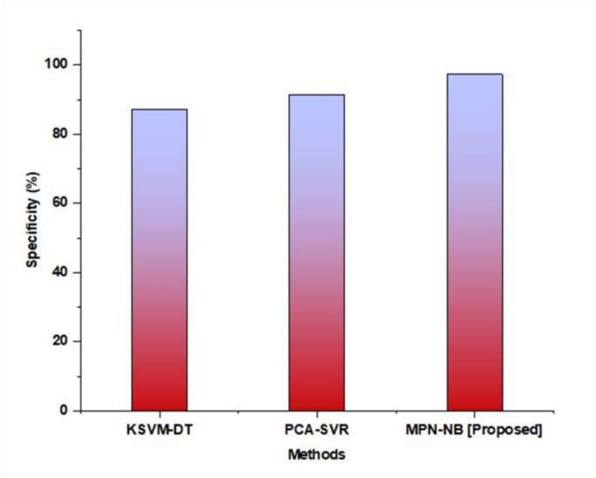

Fig 5: Specificity

The F-measure, usually referred to as the F1 score, is a statistic frequently used in binary classification and information retrieval tasks to evaluate the accuracy and the harmony between Precision and recall. It yields a harmonic mean of the two and blends accuracy and recalls into a single number.

$$F - measure \ = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (7)$$

Figure 6 shows the F-measure for the suggested and accepted approaches. The strategies suggested While KSVM-DT and PCA-SVR only receive 87.8% and 89.7% F-measure, respectively; MPN-NB receives 98.12%. The F-measure percentage of the MPN-NB technique is greater than that of traditional techniques.

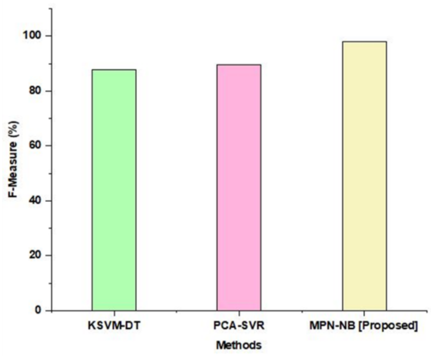

Fig 6: F-Measure

5. Conclusion

Early diagnosis of AD is essential for efficient treatment and improved patient outcomes. This research presented a modified probabilistic neural-adaptive naive Bayes (MPN-NB) for detecting AD using machine learning (ML). The proposed approach combined NB and PNN (probabilistic neural network) methods. This study examined the proposed MPN-NB technique using the ADNI dataset. The values of performance metrics for our suggested method were obtained in terms of accuracy (98.5 %), sensitivity (96.7 %), Precision (96.52), specificity (97.23 %), and F-measure (98.12 %). It has been shown experimentally that the proposed method was the most effective than the existing method in the detection of AD. In the future, we'll categorize the DCNN features using support vector machines.

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