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Applicability of Artificial Intelligence in Smart Healthcare Systems for Automatic Detection of Parkinson's Disease

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Parkinson's disease is associated with memory loss, anxiety, and depression in the brain. Problems such as poor balance and difficulty during walking can be observed in addition to symptoms of impaired posture and rigidity. The field dedicated to making computers capable of learning autonomously, without having to be explicitly programmed, is known as machine learning. An approach to the diagnosis of Parkinson's disease, which is based on artificial intelligence, is discussed in this article. The input for this system is provided through photographic examples of Parkinson's disease patient handwriting. Received photos are preprocessed using the relief feature option to begin the process. This is helpful in the process of selecting characteristics for the identification of Parkinson's disease. After that, the linear discriminant analysis (LDA) algorithm is employed to reduce the dimensions, bringing down the total number of dimensions that are present in the input data. The photos are then classified via radial basis function-support vector machine (SVM-RBF), k-nearest neighbors (KNN), and naive Bayes algorithms, respectively.

Keywords: Parkinson's disease detection, machine learning, relief algorithm, LDA algorithm, SVM-RBF, accuracy, sensitivity, specificity.

1. Introduction

Parkinson's disease (PD) is a chronic (long-term), progressive (slowly progressing), degenerative (non-reversible) neurological ailment that affects both motor and non-motor functions. It is the second most common neurological disorder after Alzheimer's disease. It targets the neurons in the brain responsible for regulating movement [1]. In the ancient Indian medical system of Ayurveda, PD is known as *kampavata* (the Sanskrit term for tremors is *kampa*), and Western medical literature recognizes it as shaking palsy. In his essay "Shaking Palsy" (1817), London doctor James Parkinson described in detail the symptoms observed in six individuals he had examined. Remarkably, his description of the motor symptoms has remained accurate and unrevised until today [2].

The condition was named by French neurologist Jean-Martin Charcot, who recognized the significance of Parkinson's pioneering work. PD's symptoms worsen over time and are more prevalent among the elderly. The root cause stems from a deficiency of dopamine in the brain [3].

The extrapyramidal motor system is affected by PD, a slowly progressing neurodegenerative disease. Dopamine and acetylcholine become unbalanced, and the substantia nigra pigmented cells begin to die, culminating in PD an extrapyramidal system condition. There is a deficiency of dopamine production in the brain, which means that the person is unable to control their movement, body and emotions [4].

There are several symptoms of PD, including tremors, lack of co-ordination, and difficulties in walking and moving. Many regions of the body can be affected by the disease. Symptoms included drooling, trouble swallowing, slow blinking, and shivering tremors and a loss of fine or minute motions affecting hands might be observed as well. Additionally, there is evidence of memory loss, anxiety, and depression in the brain. Problems such as poor balance and walking difficulties can be observed in addition to the previously mentioned symptoms of slumped posture and rigidity. Standing with a hunched or sideways-leaning posture is more common because of reduced arm and leg movements. Camptocormia, a Greek word for crooked trunk, describes this bent and leaning posture. As a result, gait and posture are impaired, causing gait freeze, postural instability, and falls [5, 6]. There is a need to develop a computer automated system for early and accurate PD detection. Such a system will help doctors and patients in taking precautionary actions to manage the disease more effectively. Although many methods are available for predicting PD, further research is needed to enhance the accuracy, precision and recall of these methods.

The study of making computers capable of learning on their own, without having to be explicitly programmed, is known as machine learning [7]. As a result of the system's design, computers are able to learn dynamically. Learning and analyzing data, building knowledge from it, and making decisions based on it are all capabilities that computers can do with the help of artificial intelligence (AI). Machine learning can be used in a variety of different ways in the medical field, and a crucial tool in the healthcare industry is a clinical decision support system [8].

This article describes a method for detecting PD using AI. The approach uses photos of PD patients' handwriting as input. First, incoming photos are preprocessed with relief feature selection. This aids in selecting appropriate features for PD detection. Then, the LDA algorithm reduces the dimensions, decreasing the number of input data dimensions. Images are then categorized using SVM-RBF, KNN, and naive Bayes. SVM-RBF performs better in PD detection.

Section 2 contains a literature survey of existing techniques for preprocessing, feature extraction, and classification. In Sec. 3, an AI-based method for automatic PD detection is presented. Section 4 provides an analysis of results from various feature selection and machine learning techniques for PD detection. Section 5 contains the conclusion and discusses future work.

2. Literature survey

This section presents a literature review of various machine learning-based techniques for PD detection. In order to deal with binary classification challenges, Kira and Rendell [9] developed the relief algorithm, an instance-based learning method, in 1992. This individual evaluation filters approach can identify feature-to-feature relationships. Nearest neighbors are used to create feature statistics that implicitly account for interactions between variables. However, this strategy does not take into account any missing values or multi-class data in the dataset.

In order to reduce the size of the original data matrix, a dimensionality reduction approach known as LDA is used [10]. Principal component analysis (PCA) is another linear transformation method, like LDA. However, PCA is an unsupervised technique in contrast to LDA, which is supervised. The fundamental goal of LDA is to discover a feature subspace that maximizes class separability, while PCA seeks the directions of maximum variance. By focusing on class-separability, LDA helps avoid overfitting and reduces computational costs.

SVMs are often used as kernel learning algorithms for high-dimensional prediction problems [11]. SVM classifiers have demonstrated superiority over other classifiers in terms of generalization and scalability. It is possible for the SVM classifier to attain somewhat robust pattern recognition performance by using a variety of commonly used statistical learning and optimization theory approaches. In the context of the SVM classifier, the main goal is to find the hyperplane with the largest error margin between positive and negative data. The distance from the hyperplane to the nearest positive or negative class is defined as the margin [12].

Massive databases are frequently classified via decision tree induction. Starting from the root node, decision trees classify data until reaching the leaf nodes [13, 14]. It is possible to develop if-then rules from the created tree, providing visual representations of rules that are easy to follow. Decision tree algorithms include ID3, C4.5, CART, and many others. One of the most effective data mining decision tree algorithms is C4.5 based on the gain ratio. Because it works well with both categorical and continuous attributes, the C4.5 algorithm is a great choice for many applications. It is also better at handling missing values and requires less memory while running large programs. Branches that are too big or too little have a negative impact on the system. On the other hand, the ID3 algorithm is built on the idea of information gain, while CART produces a binary decision tree based on the Gini Index. There are no missing values in the ID3 algorithm; hence, it works well with discrete attributes.

There are several basic algorithms for classification and regression problems, with KNN being one of the most commonly utilized. This algorithm forecasts the values of new data points based on how closely they resemble those in the training set. Known for its robustness to noisy training data it does not have a dedicated training phase and instead uses all of the data for categorization as training. In addition, it is a non-parametric approach, which means it does not make assumptions about the underlying dataset.

Writing features such as the Archimedean spiral, orthographically simple words, a sentence, and pressure on the writing surface are used in [15] to differentiate between individuals with PD and those who are healthy. This study shows that analyzing pressure on the writing surface can be used to distinguish PD from a healthy state. SVMs, ensemble AdaBoost classifiers, and KNN classifiers are used. Among these, the best classification model is the SVM.

Handwriting of a text involving on-the-surface motions as well as in-air trajectories is studied in [16]. Here, one will find kinematic elements that affect both the movements in the air and the physical contact with the surface. With the use of feature selection algorithms and SVM learning methodologies to separate PD patients from healthy controls, it was demonstrated that assessing the in-air/on-surface hand movements led to accurate classifications in 84% and 78% of subjects, respectively. However, when both modalities were combined 1% increase in accuracy was observed compared with the evaluation of in-air features alone and a medically relevant diagnosis with 85.61% prediction accuracy was obtained. Because it took into consideration both surface and air movements, the SVM approach had a classification accuracy of just 78%. However, it was possible to obtain an 85.61% prediction accuracy by combining the SVM and feature selection techniques.

Additionally, unique handwriting measures based on entropy, signal energy and empirical mode decomposition of handwriting signals were derived in [17]. For diagnosis, an SVM classifier with a radial Gaussian kernel was given just a subset of features. The results indicated the highest specificity 91%, an accuracy of 88.13%; and the most sensitive range of 89.57–89.57%. Accuracy was enhanced by the use of entropy, signal energy and other characteristics, although this approach was somewhat limited.

3. Methodology

This section presents an AI-enabled methodology for the early and accurate detection of PD. This methodology takes PD handwriting images as input. Initially, the input images undergo preprocessing using the relief feature selection algorithm. This helps in selecting the appropriate features needed for the accurate detection of PD. After that, dimensions are reduced by the LDA algorithm. This helps in reducing the number of dimensions in the input data. Then, the images are classified using SVM-RBF, KNN and naive Bayes algorithms. The proposed methodology is shown in Fig. 1.

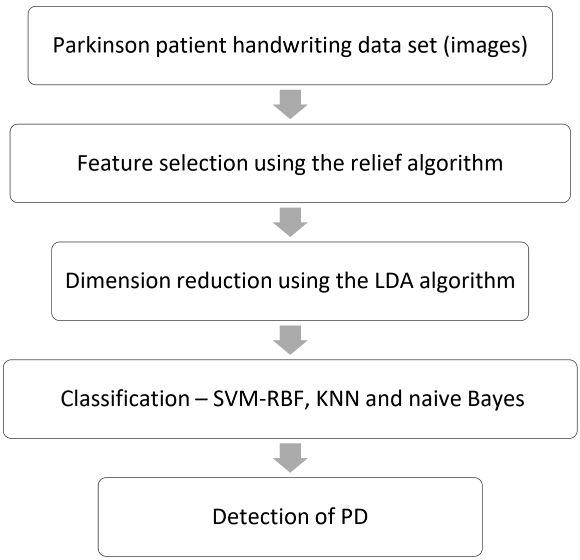

Fig. 1. AI for smart healthcare system to automatically detect PD.

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LDA is an essential component for both data classification and feature selection. It excels across various fields, including image processing, signal and audio processing, and face recognition, to name just a few of those fields. A discriminant analysis is carried out as part of this research project in order to classify aspects of speech as either intellectual disability (ID) or typical development (TD). LDA is employed in order to accomplish the aforementioned goal of increasing class separability margins in a space with fewer dimensions [10]. The mathematical concept of linear transformation refers to the process of changing the acoustic features vector into the projection features vector. There are similarities between LDA and logistic regression. Given all of the requirements, LDA performs better than logistic regression even with very small datasets. The primary challenge lies in implementing LDA in higher dimensions, where issues such as the well-known curse of dimensionality arise due to geometric aberrations that occur in high dimensions. Incorrect use of the concentration of measure might make calculations more difficult than they need to be.

Classifiers using the naive Bayesian approach are based on simple assumptions about the relationships between predictors, such as independence. There are no iterative parameter estimations in a naive Bayesian model, making it ideal for large datasets. Despite its simplicity, the naive Bayesian classifier often outperforms more advanced classification algorithms and is therefore widely employed [18].

The KNN classification, also known as instance-based learning (IBK), organizes occurrences based on how closely they are related to one another. It is one of the most widely used algorithms for recognizing patterns in data. In this type of lazy learning, the function is only approximated locally, and full computation is deferred until classification. The majority of nearby objects classify an object as one of a certain type. It is safe to state that k is always assumed to be a positive number. Classification information is used to select neighbors from a known set of items. In WEKA, this classifier is known as IBK (instance-based learning). Continuous-valued target functions are suited for the KNN method, computing the average by averaging the values of the k-closest neighbors. The KNN is a distance-weighted algorithm [19].

Computational learning theory is behind the SVM learning technology. The SVM's primary objective is to find the best classification function for classifying the training dataset into categories. Classification challenges such as density estimation and pattern recognition can be solved using SVM as a classification model. In the first step, SVM performs a nonlinear mapping of the training data into a higher dimension, and then separates the two dimensions linearly [20]. RBF is a preferred choice.

The complexity of SVM is as follows:

$$\text{Training time complexity } = O(n^2),$$

$$\text{Run-time complexity } = O(k \times d),$$

where n is the number of training examples, k is the number of support vectors, and d is the dimensionality of the data.

4. Results and discussion

There are a total of 77 occurrences included within the input data set [21, 22]. Among these, the last 15 photographs represent healthy persons' handwriting, whereas the first 62 represent individuals' handwritings with Parkinson's disease. There are a total of sixty photos used for training purposes. In this research, the overall performance of various algorithms is evaluated based on three main parameters: accuracy, sensitivity, and specificity. Figure 2 illustrates the degree of accuracy achieved. In addition, sensitivity and specificity criteria are used in the process of measuring the effectiveness of machine learning algorithms. Figures 3 and 4 illustrate the sensitivity and specificity of the SVM, RBF, KNN, and naive

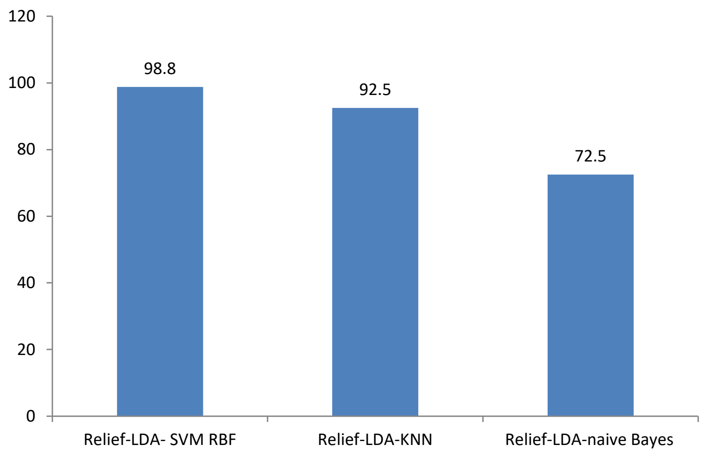

Fig. 2. Accuracy of relief-LDA-SVM RBF, relief-LDA-KNN and relief-LDA-naive Bayes classifiers.

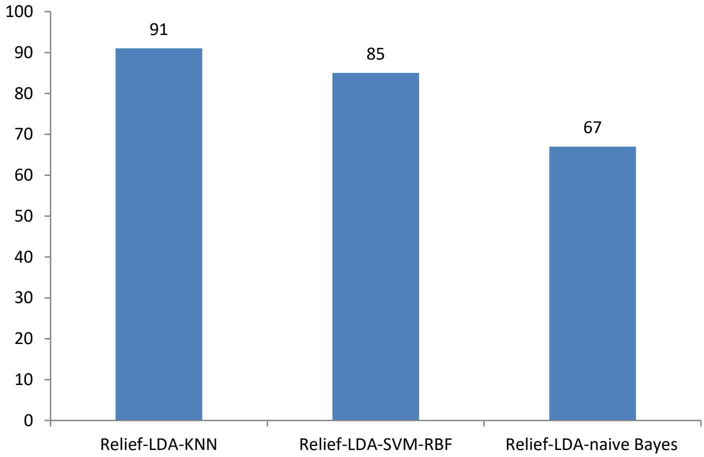

Fig. 3. Sensitivity of relief-LDA-SVM RBF, relief-LDA-KNN and relief-LDA-naive Bayes classifiers.

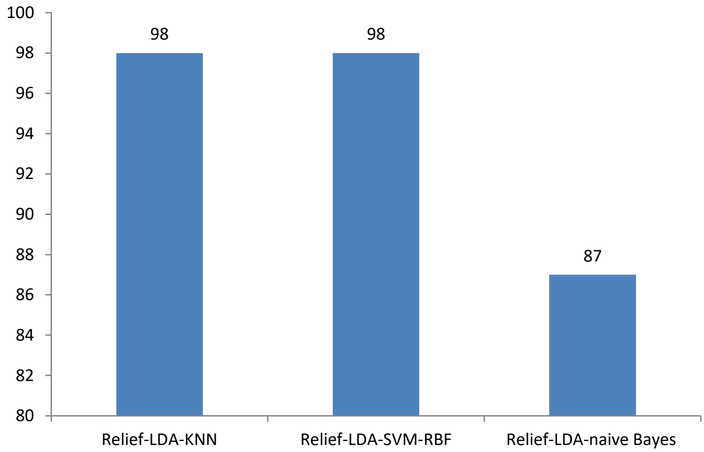

Fig. 4. Specificity of relief-LDA-SVM RBF, relief-LDA-KNN and relief-LDA-naive Bayes classifiers.

Bayes models, respectively. Accuracy of the relief-SVM-RBF algorithm is better, while the KNN algorithm exhibits better sensitivity and specificity:

$$\begin{aligned} \text{Accuracy} &= (\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN}), \\ \text{Sensitivity} &= \text{TP}/(\text{TP}+\text{FN}), \\ \text{Specificity} &= \text{TN}/(\text{TN}+\text{FP}), \end{aligned}$$

where TP – true positive, TN – true negative, FP – false positive, FN – false negative.

5. Conclusion

PD is a chronic, progressive and degenerative neurological condition that affects both motor and non-motor functions. PD manifests itself in a variety of ways, including tremors, lack of coordination, and difficulties in movement. The disease has the potential to affect many different parts of the body. From facial symptoms such as drooling, difficulty in swallowing and slow blinking to motor issues such as shivering tremors and loss of fine or minute movements in the hands, Parkinson's disease has diverse impacts. In addition, memory loss, anxiety, and depression are present in the brain. Moreover, in addition to the previously mentioned symptoms of slumped posture and rigidity, other issues such as poor balance and difficulty in walking can be observed as a result of this condition. Machine learning is the study of how to make computers capable of learning on their own, without having to be explicitly programmed, and is a branch of AI. Unique to this approach, this article introduced a method for detecting PD by using photos of PD patients' handwriting as input. Initially, all incoming photos were preprocessed using the relief feature selection. This assisted in the selection of features for PD detection. After that, the LDA algorithm was used to reduce the dimensions. It reduced the number of dimensions in the data that is being processed. The images were then classified using SVM-RBF, KNN, and naive Bayes algorithms. Accuracy of the relief-SVM-RBF algorithm was better, while the KNN algorithm provided better sensitivity and specificity.

Given the problems that currently exist in PD subtype differentiation, severity assessment, and prognosis, exploring machine learning in neurodegenerative illnesses, as presented in this study, holds promise for a better understanding of such illnesses.

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