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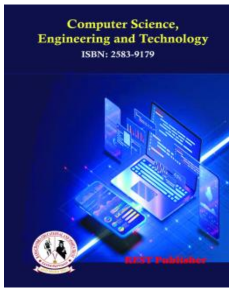

# Prediction of Parkinson Diseases at Early Stage Using Deep Learning Method

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***Abstract:*** *The second most prevailing neurodegenerative disorder is Parkinson's disease (PD) that have been affected nearly 6 million of people in the world. The availability of emblematic treatment has the ability to increase the survivability of disease but there is no curing treatment available. The PD predominance and the disability life years are endured to increase steadily that may lead to a viable burden on patients and their families. Dopaminergic medications can typically slow down the PD progression whileused during the earlier stages. Theses treatment is frequently become less efficiency with the disease progress. Diagnosis of PD at early state is essential for immediate interventions which assist the patients to remain self-sufficient with long time period probably. Disturbances of balance, gait and posture are a hallmark of parkinsonian syndromes. Specifically, to uncover PD at an early stage, several indicators have been considered by testing the person by Neuro-radiological tools, cognitive tests, freezing of gait questionnaire and Movement Disorders Society- Unified Parkinson's Disease Rating Scale (MDS-UPDRS). In this paper,the proposed fuzzy logic approach for prediction of PD and their severity classification withLong Short Term Memory (LSTM) is utilized for overcoming the curse dimensionality. The dataset involved consists of both numerical and categorical data which performs classification of PD patient at early stage by categorical data. Based on LSTM, the fuzzy rule get generated and the fuzzy logic computation technique is depend upon degree of truth. Using fuzzy logic the accurate prediction of PD at early stage and its level of severity is identified based on fuzzy rule with LSTM with accuracy of 96.5%.*

***Keywords:*** *Parkinson Disease (PD), Diagnosis test, Magnetic Resonance Imaging, Fuzzy logic rule, Long Short Term Memory (LSTM), Diagnosis test.*

## 1. INTRODUCTION

PD has a large global impact that influencing millions and manifesting as a gradually severe condition defined by a gradual appearance of symptoms. Although explicit indicators are most prevalent among adults above 50 years, one in every ten people develops PD symptoms before the 40 years age [1]. The primary pathophysiology of PD is the degradation of particular nerve cells in the brain's significant nigra. These cells have produce dopamine, a neurotransmitter crucial to controlling physiological motions, are fading away, resulting in a lack of this essential molecule. Dopamine deficiency establishes the scene for a gradual development of a wide range of progressive PD symptoms. Initial symptoms frequently involve tremors or stiffening on either side of the body and most commonly afflicting the hand or arm. As the condition advances, it may lead to the emergence of dementia in its later stages and complicating the issues experienced by those with PD [2]. Between 1996 and 2016, the global occurrence of PD increased dramatically, from 2.5 million to an astounding 6.1 million cases. This surpassing substantially growth is inextricably related to the increase in lifespans, resulting in a globe with a rapidly ageing population [3]. The brain play as the primary control hub of the body, manages a complicated relationship with diverse bodily systems. PD causes a wide range of distressing symptoms, including either a complete or partial impairment of motor responses, speech problems that may result to permanent collapse, abnormal behavioral patterns, cognitive impairment, and the deterioration of other crucial abilities [4]. In 2017, the projected economic effect of PD in the United States was $51.9 billion. This complete study included indirect expenditures of $14.2 billion, non-medical charges of $7.5 billion, and an extra $4.8 billion for people with disabilities related to public works. Considering that a significant number of people with PD are 65 and older age, forecasts show that the complete financial impact will rise to about $79 billion by 2037 year [5]. The present PD diagnostic landscape, as stated by the National Collaborating Centre for Chronic Conditions in 2006, is mainly reliant on invasive methods, tests that are empirical, and detailed investigations. Aside from improving diagnostic precision, the primary objective of this study is to possibly decrease a portion of the cost constraints related to PD management. The project aims toward contributing to a more effective and affordable paradigm for identifying and treating the difficulties of PD in future generations by innovative as well as non-invasive technologies [6]. Many research investigations in neuroimaging have investigated several non-invasive brain scanning approaches, such as functional Magnetic Resonance Imaging (fMRI) and diffusion MRI (dMRI), in an effort to deal with the issues given by autism spectrum disorder (ASD) [7]. Although, these investigations are greatly improved the comprehension of both functional as well as structural connection modifications in the brains of individuals with ASD. The results have mainly ignored the subtle morphological modifications that occur among distinct brain regions [8]. Understanding a need in the network neuroscience field, current initiatives have investigated into the possible application of Cortical Morphological Networks (CMNs) obtained solely from T1-weighted MRI as a method of distinguishing among the cortex of people with autism and those took into account as an usual [9]. Particularly, previous research has examined morphological modifications at the particular level in the regions of brain. However, many researches have come up with lack in exploring the dynamic changes in a particular Region of Interest (ROI) in relation to other. Conversely, the morphological links among pairs of ROIs may be efficiently characterized by morphological brain networks, since the connectivity among two regions captures their morphological difference, a recently introduced notion in the field [10]. This technique provides a more detailed view of the subtle morphological alterations noticed at the intersection of particular brain regions in those suffering from ASD, highlighting a critical component that previous investigations had ignored. Therefore, this study initiative aims to diagnose PD using advanced Machine Learning (ML) and Deep Learning (DL) methods. The major goal is to identify among healthy individuals and those with PD by utilizing various features retrieved from signals from their voices. The prospective outcome intends not only to improve diagnostic accuracy, but additionally to help reduce related monetary costs. The article is divided into distinct chapters are as follows. In Chapter 2, we explore various methods sourced from previously published articles. Moving on to Chapter 3, we delve into the utilization of datasets and the formulation of our proposed model architecture. Chapter 4 is dedicated to the discussion of the experimental results and the ensuing analysis. Finally, Chapter 5 addresses the conclusion of the study and outlines areas for future work.

## 2. LITERATURE REVIEW

This section has discusses the review of various previous endeavors to use DL and the fuzzy logic rule for detecting the PD which even detect the earlier stage of PD. This can be done through several testing that get discussed for the analysis of research. The proposed diagnostic strategy combines selection as well as classification techniques in a fluid manner, using complex techniques including Feature Importance and Recursive Feature Elimination in the critical work of Feature Selection (FS). During extended experiments, a wide range of ML methods was employed, including the flexible features of Artificial Neural Network (ANN), Support Vector Machine (SVM), and Decision Tree (DT). The resulting method acted as beneficial instruments in the complex process of classifying people with PD. After meticulously evaluating the effectiveness of different ML algorithms, it became clear that SVM, especially when combined with Recursive Feature Elimination produced better outcomes. This novel strategy resulted in a remarkable accuracy rate 93.83%, obtained by utilizing the smallest number of voice parameters required for PD [11]. The remarkable efficiency of this technique highlights its possible importance in this field of neurodegenerative disease classification, providing a viable route for the development and development of the diagnostic process in the interest of better results for patients. The findings from the use of ANN and SVM as methods of diagnosis for PD specialists show a high level of accuracy, estimated to be about 90.08%. These advanced ML models make a substantial contribution to the process of diagnosis, as evidenced by their ability to help healthcare providers effectively recognize and assess PD cases [12]. This high accuracy is not just demonstrates the trustworthiness of these computational techniques, yet it additionally carries positive implications for improving the accuracy and effectiveness of testing techniques in the field of PD detection. In order to delve deeper toward these findings, it's made clear that leveraging ANN and SVM is an invaluable resource in continuing attempts for improving the diagnostic landscape as well as patient care in PD field [13]. In order to accurately diagnose of PD and efficiently identify individuals in good health, a thorough examination of several classification systems was conducted. The research was intended to determine the best method for accurately discriminating among afflicted and unaffected individuals. During the process, a rigorous comparison study was performed, applying four distinct categorization methods in a preset order such as DT, Regression, NN, and ANN. Each classification method was thoroughly evaluated utilizing a variety of assessment techniques has resulting in an exhaustive comprehension of their distinct performances. Particularly, amongst these classifiers, the NN outperformed the others, as seen by consistently greater application scores across multiple assessment parameters. The NN's ability to capture complex patterns and deep interactions within the information emerged clear, establishing it as the top performance in the diagnostic setting. This outstanding results was complemented by the NN's amazing total accuracy in classification, which reached an astonishing 92.91% [14].

Additionally, the statistical techniques benefits like the receiver operating characteristic (ROC) curve assist in identifying the disease continuously monitored using ANN has deduced the causes of PD [15]. Fuzzy K-NN (FKNN) is other well-known classifier which numerous investigators have depended upon, as it is based on proximity as well as relevance of the retrieved characteristics [16]. An approach that has not gained widespread acceptance is feature weighting using FCM Fuzzy Weight (FCMFW) with respect to the biggest influence of the feature retrieved from the identical group or class and was employed to diagnose PD in its earliest stages [17]. The KNN classifier uses nearby points as the starting point and grows from there for categorizing the region that has been diagnosed is another technique that has had a positive influence on the early identification of PD. One application which utilized extracting groups with sub-specifications was Principal Components Analysis (PCA) [18]. Actually, the Beta-elliptical technique as well as the fuzzy perceptual detector has been used for feature extraction in a variety of applications, including writer identification, character recognition and signature verification [19]. Actually, the Beta-elliptical method is founded on an explanation that combines two aspects are

1. Beta functions describe the velocity profile in the dynamic domain
2. Elliptic arcs that define the handwriting trajectory in the static domain [20].

Furthermore, the fuzzy perceptual detector is an established technique for evaluating handwriting papers by looking for the presence of unusual visual characteristics.

## 3. RESEARCH METHODOLOGY

The technique proposed in this research work major goal is for identifying PD in the earlier stage that may assist the patient in minimizing the growth of PD progression by controlling it by medications, exercises, etc. The study is executed through various clinical testing like detection of structural MRI and dopaminergic radiotracer imaging with Single Photon Emission Computed Tomography (SPECT) or Positron Emission Tomography (PET). This concept applies an efficient technique to identify the patients are healthy or PDs in earlier stage using historical data.

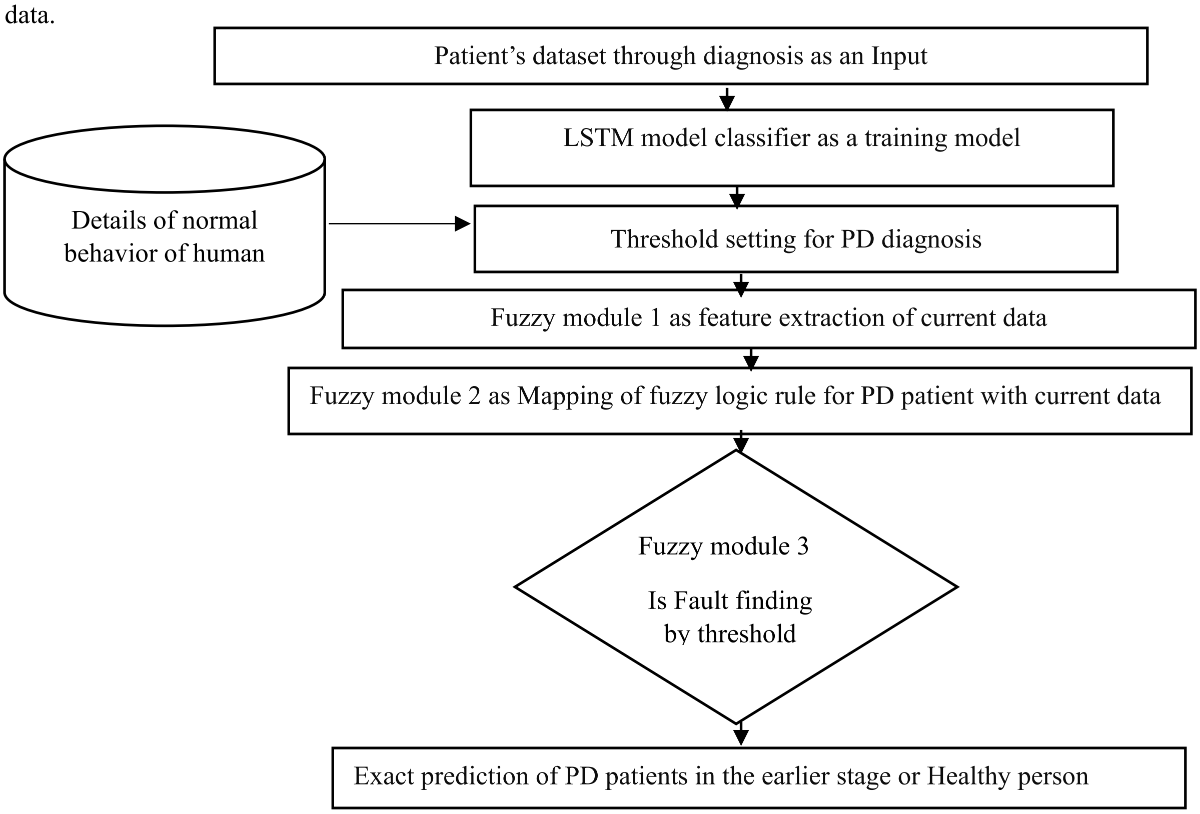


**FIGURE 1.** LSTM-Fuzzy logic as proposed architecture for earlier finding of PD patients

The clinical evaluation and PD imaging analysis is critical for the PD diagnosis. In the earliest phases of PD, neuronal death begins in the ventrolateralsubstantianigra pars compacta, subsequently spreads to the posterior putamen as well as other parts of the striatum. Furthermore, dopaminergic radiotracer imaging with SPECT or

PET serves as a biomarker for earlier PD, detecting dopaminergic denervation in the pre-motor phase. Therefore, this proposed method is used to identify and characterize crucial notation contain three steps are

1. Fuzzy-logic based mapping
2. Feature extraction
3. Fault finding point

Before getting into the fuzzy logic rule functions, the input of the normal behavior of individual person for both male as well as female is trained into an architecture of Recurrent Neural Network (RNN) as Long Short Term Memory (LSTM) method. This technique has assisted to predict the earlier stage precisely from normal behavior of human but PD stage can be determined through Fuzzy logic rule which is useful in identifying the anomaly occurrence in the analysis of specific moment has shown in Figure 1. The estimated traffic is unlikely to be identical to the actual traffic. However, it has become vital to establish thresholds among expected as well as real traffic. Bienaymé-Chebyshev's discrepancy is employed for determining the difference among the predicted and actual values. BienayméChebyshev's inequalities establishes a data percentage has limited is within a number k of standard deviations of the mean value. When the distributions of data are uncertain, outliers may be detected using the degree of inequality. Let's employ fuzzy approaches to convert these informal assertions into precise vocabulary. To transform the following casual statement into accurate words, a fair notion is to employ fuzzy techniques that have been developed specifically for this purpose.

**Fuzzy module 1: Feature extraction of current data**

The major goal of step involved in feature extraction is about computing a quantitative features set of the local MRI structure at every position of pixel position which may assist to discriminate among various types of crucial points. When the MRI image structures has generally envelope a specific image portion that can be avoided an unwanted computations by initial performance step of foreground selection.It has discarded theMRI image locations which is not probable to manage neuronal structure and maintain only the region that is suitable for future examination.

However, the focal point selection is determined in case of a pixel location (m, n) in a provided MRI as I that need to be studied as forefront or setting and analyzing the variation of limited intensity as ρ(m, n) over a radius of circular neighborhood $r_{cn}$ centered at specific location. Hence, the strong assumption get avoided in the local intensity allocation by choosing the benefit of distinction among 90th and 10th percentile of intensities present in the neighborhood as the variation measures is shown in equation 1, equation 2 and equation 3.

$$\delta(m,n) = \mathrm{P}_{90}(I_{mn}) - \mathrm{P}_{10}(I_{mn}) \quad (1)$$

$$I_{mn} = \{I(x,y)|(x-m)^2 + (y-n)^2 \leq r_d^2\} \quad (2)$$

$$m,x \in [0,w-1] \; and \; y,n \in [0,H-1] \quad (3)$$

Where,

W = width of the I in pixels

H = Height of the I in pixels

In addition, the ρ represent the relative coefficient value whereas the equal or less than the threshold value is healthy person and greater than threshold value is defined as PD at earlier stage based on the severity. Hence, the histogram ρ has been computed for the complete image consists of two clusters namely foreground and background pixels that can be separated by percentile threshold. The percentage should be determined so that as many pixels in the background (True Negative (TN)) as feasible are deleted while as many pixels in the foreground (True Positive (TP)) are maintained in reality, this means there are False Positive (FP). The ensuing collection of foreground pixel positions is designated as False Negative (FN).

In the case of angular profile analysis in MRI get executed for each chosen foreground location in which the local angular profile has measured as well as analyzed. The fundamental task is for assessing the occurrence as well as all curvilinear image structures properties present in the MRI has passed through the given location. Finally, the MRI and SPECT have correlated the image with oriented kernels set which get distributed consistently in angles range over the location. The general kernel utilized for intent is size with D ×D pixels is a constant profile in single direction and an orthogonal direction with Gaussian profile is shown in equation 4.

$$G(m,n) = e^{{}^{-x^2}\!/_{2\sigma_D^2}\!/_{S}} \quad (4)$$

 

Where,

S = Normalization factor with sum of G(m, n) in all kernel pixels

Hence, this research has considered the Gaussian together due to it has observed in which the axons and dendrites of cross-sectional profile for applications is about Gaussian and even the Gaussian has analyzed to be a familiar filter to regularize purposes. Moreover, parameters like D and σD have determined the size as well as shape of the kernel profile which is associated with the estimated branch diameter. Thus the kernel is utilized for computing local angular profile at all pixel location (m, n) in the given MRI and SPECT as I has shown in equation 5.

$$P(m,n,\alpha,k,D) = \sum_x \sum_y I\left(m_{x,y}, n_{x,y}\right)\ G(x,y) \tag{5}$$

The transformation of MRI and SPECT image coordinates get accomplished is shown in equation 6.

$$\begin{bmatrix} m_{x,y} \\ n_{x,y} \end{bmatrix} = \begin{bmatrix} m \\ n \end{bmatrix} + kD \begin{bmatrix} \sin\alpha \\ -\cos\alpha \end{bmatrix} + \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{6}$$

The summation has performed all kind of (x, y) kernel with defined and the image correlation with kernel path as $P(m,n,\alpha,k,D)$ get rotated with an angle $\alpha$and moved over a distance kD depends on the direction with respect to the angle. Moreover, the parameter k is normally set somewhat larger than 0.5 for scanning the neighborhood in the measured pixel (x, y). Hence, the image intensity has accomplished at non-integer transformed location $\left(m_{x,y}, n_{x,y}\right)$ with the utilization of linear interpolation.

**Fuzzy module 2: Fuzzy Logic (FL) Based Mapping**

The extracted feature values for every foreground MRI and SPECT locations are finally required to progress for assessing the crucial point and its types. This is a matter of degree for recognizing completely and allow to map nonlinear input as well as output. Fuzzy logic has been proposed for this research that are succeeded in several engineering areas but best in exploring for MRI and SPECT is not considered in fault finding analysis. The general description of FL has presented certain FL system to calculate crucial point mapping of MRI and SPECT images. In a FL system, numerical inputs have initially uttered in linguistic terms is said to be fuzzification followed by the process of inference with respect to predefined rules for generating linguistic outputs. Finally, the linguistic output is converted into numeric values by defuzzification process.

Fuzzification process has performed an input scalar value s ∈ R then it resulted in a vector $\tilde{s}$ whereas the elements are express in term of membership degree and s to input fuzzy sets. Each correspondence with linguistic term described as s. A fuzzy set can be definite using a membership function μ : R → [0, 1] that quantify the degree s and it is described through the respective linguistic term. In general, the utilized function of membership functions namely piecewise linear, Gaussian, trapezoidal and triangular. The linguistic terms is represented as Low and High has represented the individual notions "Less than threshold" and "More than threshold" respectively. The outcome of fuzzification process is expressed in equation 7.

$$\tilde{s} = [\mu Low(s), \mu High(s)]^T \tag{7}$$

The interference process of an input fuzzy set memberships have been progressed using the inference engine for generating rules for fuzzy as an output that express the skilled knowledge. The rules may either defined implicitly or explicitly that has been learned through LSTM classification training dataset and expresses nonlinear relationship of input and output which consists of multiple inputs. In engineering applications, the rules are generally provided as IF-THEN statements based on the linguistic term of input as well as output is expressed in equation 8.

$$R_i : IF\ (s1 = High) \wedge (s2 = Low) THEN\ (\zeta = OFF) \tag{8}$$

Where,

z∈ R, the variable in the output range which is not a statement of binary logical. The input as well as output conditions are in the form of true or false, but a fuzzy logical statement conditions expressed with respect to memberships. According to the equation 8, μHigh(s1), μLow(s2), as well as μOFF(z) are considered and the input circumstances are frequently combined by operators ∧that is denoted as fuzzy intersection. This defined the argument of minimum and maximum and $R_i$ with IF-part may result in subsequent intermediate degree of verity is expressed in equation 9.

$$\nu_i = min\{\mu\text{High}(s1), \mu\text{Low}(s2)\} \tag{9}$$

This value is utilized for constraining the fuzzy set with respect to the output linguistic term has addressed by $R_i$, in this case OFF is resulted in the output fuzzy set is expressed in equation 10.

$$\Upsilon_i(\zeta) = min\{\mu\text{OFF}(\zeta), \nu_i\} \tag{10}$$

Basically, several rules such as $R_i$, i = 1,...,NR, that get aggregated through inference engine for generating single output fuzzy set ϒ whereas the mean of weighted fuzzy union is considered and expressed in equation 11.

$$\Upsilon(\zeta) = max\{\omega_1\gamma_1(\zeta), \omega_2\gamma_2(\zeta), \ldots., \omega_R\gamma_R(\zeta)\} \tag{11}$$

However, it is probable in assigning a dissimilar weight for each rule by setup $\omega_i \in$ [0, 1], in this applications which is not virtual and therefore it has utilized $\omega_i$ = 1 for all i.

Finally, the defuzzification process execute the fuzzy logic system with an output of fuzzy as ϒ has been converted into a scalar output value. In addition, there are several ways to execute the method for calculating the centroid is expressed in equation 12.

$$\hat{\zeta} = \frac{\int \zeta\gamma(\zeta)d\zeta}{\int \gamma(\zeta)d\zeta} \tag{12}$$

With this value we can finally calculate the vector of output fuzzy set memberships: $\tilde{\zeta}$ = [μOFF($\hat{\zeta}$), μ ON($\hat{\zeta}$)] $^T$

**Fuzzy m**odule **3: Fault finding point**

To assess the presence as well as type of crucial point at every foreground image position, researchers employ a cascade of two fuzzy-logic methods with two assessment levels. Initial level considered as input vectors si = [li, ui, ci], i = 1,..., 4, contain the features to each of the extracted streamlines step for angular profile analysis in image location ("Angular Profile Analysis"). Every streamline, the features have fuzzified (μ) as well as process by the initial FL module (FL1) that establish the degree in which the streamline certainly represent a line-like image structure (ON), or not (OFF). When the angular profile analysis step finds less than four streamlines, the feature vectors of the nonexisting streamlining are set to 0. The fuzzy output from all four streamlines serves as the input for the subsequent decision level, wherein second FL module (FL2) assesses if the image location belongs to a junction (JUN), a termination (END), or neither (NONE).The non-existing feature vectors streamlines are set to be zero. The fuzzy output from all four streamlines serves as the input for the subsequent decision level, wherein FL2 assesses if the image location belongs to a JUN, END, or NONE. The final goal for this method is to generate a list of crucial spots in the neuron image, each of which is thoroughly defined with respect to type, location, size, and main branch direction. Because each crucial location of a neural tree often encompasses numerous surrounding pixels in the image, resulting in a high value at the pixels that correspond in the maps $I^{END}$ and $I^{JUN}$, the last phase is for segmenting the maps as well as accumulates the data inside for each segmented region.

## 4. RESULTS AND DISCUSSION

The technique to this research used LSTM to shape an issue in predicting univariate time series. In this approach, LSTM determines the signature of typical behavior in networks. An LSTM has been applied to each previously determined flow feature, implying that each LSTM will be in charge of predicting the typical behavior signature for each feature. The LSTM algorithm will train a function that converts a sequence of n prior input data toward output data. To boost robustness, initially regulate the scores of real-valued in the maps using local-average filtration with radius 3 to 5 pixels. The maps are then segmented using max-entropy-based automatic thresholding, that, unlike several other thresholding methods has performs effectively in distinguishing between large but relatively flat background areas and significantly smaller yet continuously changing RoI. The generated binary images are then analyzed by a typical interrelated component technique for finding critical-point locations.

The system has been developed in Python and incorporates development libraries for DL Keras and TensorFlow. The experiments have been carried out in a setting containing as follows

1. Intel Core i5 2.21 GHz processor
2. 8 GB RAM
3. Windows 10 operating system

The right and wrong hits, as well as the detection misses, were counted in relation to the reference data to quantify performance. We carefully counted the TP, FP, and FN critical-point detections. Formula for confusion matrix metrics is calculated as follows Recall (R) = TP/(TP + FN) and Precision (P) = TP/(TP + FP). Both R and P take on values in the range from meaning total failure (0) to meaning flawless detection (1). They are generally combined in the F1-score is defined as the harmonic mean of the two is formulated as F = 2RP/(R + P). The F1-score was calculated individually for each type of crucial point examined in this work, producing $F^{END}$ to terminations and $F^{JUN}$ to junctions.

**TABLE 2.** Confusion matrix for proposed method with traditional method

| Algorithm | Confusion Matrix | | | |
|---|---|---|---|---|
| Random Forest (RF) | | **$CR_0$** | **$CR_1$** | **Total** |
| | **$CR_0$** | 106 | 46 | 152 |
| | **$CR_1$** | 6 | 49 | 55 |
| Fuzzy logic | | **$CR_0$** | **$CR_1$** | **Total** |
| | **$CR_0$** | 144 | 8 | 152 |
| | **$CR_1$** | 4 | 51 | 55 |
| Fuzzy - LSTM | | **$CR_0$** | **$CR_1$** | **Total** |
| | **$CR_0$** | 146 | 6 | 152 |
| | **$CR_1$** | 2 | 53 | 55 |
| ANN | | **$CR_0$** | **$CR_1$** | **Total** |
| | **$CR_0$** | 139 | 13 | 152 |
| | **$CR_1$** | 4 | 51 | 55 |
| SVM | | **$CR_0$** | **$CR_1$** | **Total** |
| | **$CR_0$** | 137 | 15 | 152 |
| | **$CR_1$** | 5 | 50 | 55 |

$CR_0$ = Patient with PD

$CR_1$ = Healthy Person

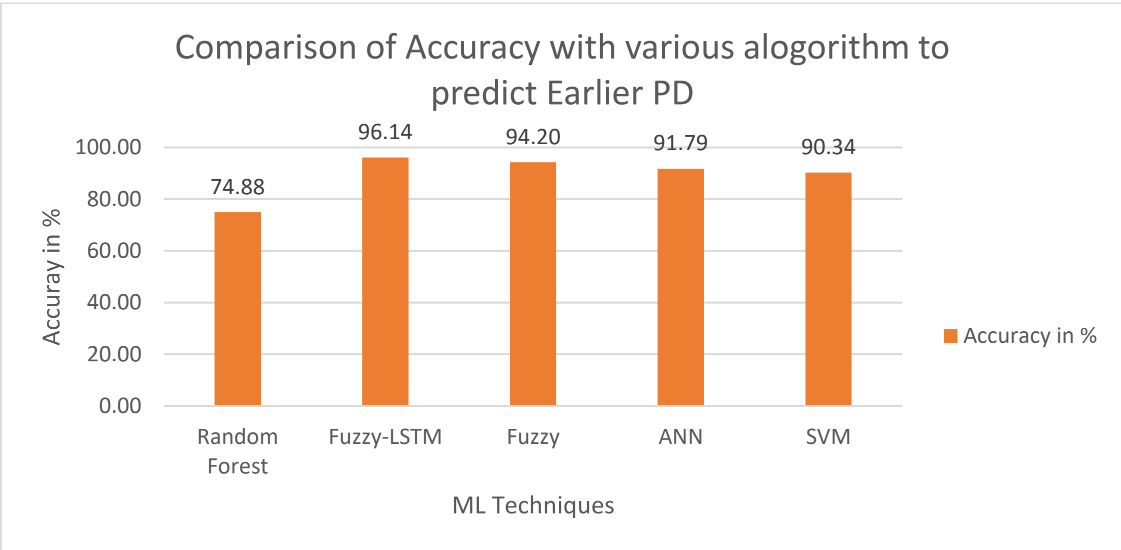


**FIGURE 2.** Comparison of accuracy with various ML techniques in earlier prediction of PD

Figure 2 illustrates the accuracy of Fuzzy-LSTM method in prediction of PD is 96.14% which is higher than fuzzy, ANN, SVM and RF are 94.20%, 91.79%, 90.34% and 74.88% respectively. This determines that Fuzzy-LSTM method can able to diagnose the PD earlier better when compared with usage of other method application.

 

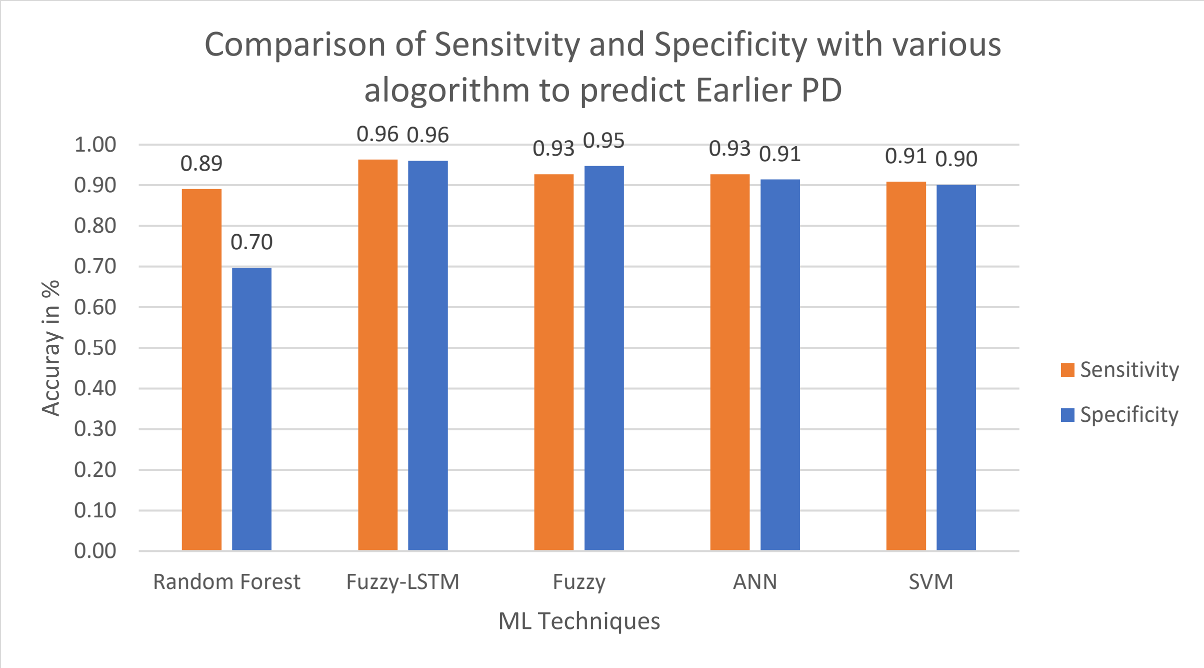


**FIGURE 3.** Comparison of Sensitivity and Specificity for earlier prediction of PD method

Figure 3 illustrates the sensitivity and specificity score of Fuzzy-LSTM method in prediction of PD is 0.96 and 0.96 which is higher than fuzzy, ANN, SVM and RF are 0.93 and 0.95, 0.93 and 0.91, 0.91 and 0.90 as well as 0.89 and 0.70 respectively. This determines that Fuzzy-LSTM method can able to diagnose the PD earlier better when compared with usage of other method application.

## 4. CONCLUSION

The researchers proposed a novel method for finding and describing crucial places in tree-like patterns in neuron based microscopy images. It presents a combined structure for identifying both terminations as well as junctions at the same time, employing a directional filtering and FE method and a two-stage FL-based reasoning system. Based on the results of trials on both simulated and real fluorescence microscopy images of neurons and conclude that the approach developed obtains significantly better detection rates than those predicted by existing neuron reconstructing techniques. The initial is in charge of traffic characterisation, created an innovative method to forecast the usual network behavior operation by employing an LSTM semi-supervised approach with IP flows. The subsequent module, the provided mechanism for recognizing attacks using Bienaymé-Chebyshev's inequality and FL. Lastly, final module get implemented automated mitigation rules for minimizing the harm resulting from assaults while maintaining network operational requirements. For verification of the development system, it used two instances with distinct features. Based on the findings, the Fuzzy-LSTM has outperformed all others with a low FP rate and good precision, recall, and AUC rates.

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