Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 4s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

Parkinsons Disease Prediction With Spiral Drawings and Wave Frequency Using Deep Conformal Neural Networks

Mrs. S. SasiRekha[1], Dr. R. Shankar[2], Dr. S. Duraisamy[3]

[1]Research Scholar,

[2]Associate Professor,

[3]Assisstant Professor

[123]Department of Computer Science,

[123]Chikkanna Government Arts College, Tirupur, India

Cite this paper as: Mrs. S. SasiRekha, Dr. R. Shankar, Dr. S. Duraisamy, (2025) Parkinsons Disease Prediction With Spiral Drawings and Wave Frequency Using Deep Conformal Neural Networks. *Journal of Neonatal Surgery*, 14 (4s), 11-22.

ABSTRACT

In this study, present a system that combines two independent data sources wave frequency and spiral drawing picture datasets to improve prediction accuracy for Parkinson's disease (PD) diagnosis. A complete data fusion technique is used to combine information from both modalities, resulting in a more robust dataset. To improve prediction reliability, we present Deep Conformal Neural Networks (DCNN), which not only forecast PD status but also offer confidence ratings for each prediction, resulting in increased transparency and interpretability. The technology uses voice recordings for frequency analysis and picture data from medical scans for visual analysis. The DCNN model successfully processes and classifies different data types by using sophisticated deep learning methods such as convolutional operations, pooling layers, and activation functions. The model's performance is assessed using a variety of measures, including accuracy, precision, recall, and F-measure. The DCNN surpasses standard machine learning models, with 99% accuracy, 98% precision, 99% recall, and 96% F-measure, exhibiting greater diagnostic skills for Parkinson's disease diagnosis. These results emphasize DCNNs' potential for enhancing the reliability of early Parkinson's disease diagnosis, hence facilitating more effective clinical decision-making.

Keywords: *DCNN, Parkinson's disease (PD), Spiral Drawing, Wave Frequency, Early Prediction*

1. INTRODUCTION

After Alzheimer's disease (AD), Parkinson's disease (PD) is said to be the second most often occurring neurological illness of the central nervous system. PD targets older adults primarily with ages of 60 years or more. Including their death, neurodegenerative illnesses cause structural and functional loss of the neurons. Second frequency in neurodegenerative diseases is Parkinson's disease (PD). First mentioned in James Parkinson's 1817 publication "An Essay on the Shaking Palsy," PD. Many of the created Machine Learning and Deep Learning models by --different researchers are seen as automated approaches facilitating Parkinson's disease detection Ali et al. (2019). Though certain medications assist to reduce the symptoms and preserve the quality of life, there is no correct therapy for PD diagnosis. Those therapies include physiotherapy, drugs, and surgery. Parkinson's diagnosed using cardinal motor indications of stiffness, tremor, and instability. Examining this face expression is more consistent and simpler as well as it utilized widely in telemedicine, thus affecting the patents on the faraway areas.

Mostly affecting motor skills including movement, balance, and coordination, Parkinson's disease (PD) is a progressive neurological illness. Using several modalities including voice signals, gait patterns, handwriting, and face recognition, recent developments in machine learning (ML), deep learning (DL), and feature engineering greatly improve early identification and prediction of Parkinson's disease.

Increasing amount of studies has concentrated on PD identification utilizing handwriting and art patterns. We developed a robust cascaded learning system using feature selection and adaptive boosting, which demonstrated remarkable accuracy in recognizing Parkinson's disease from handwritten illustrations. In line with this, Karan et al. (2020) used speech signal intrinsic mode function-based features for PD prediction, therefore highlighting the possibilities of multi-modal feature extraction for precise diagnosis.

Advanced neural networks including LSTMs and CNNs have been used recently for PD prediction. Emphasizing the potential of speech analysis in neurological diagnostics, Anila et al. (2024) suggested an LSTM-based deep neural network model using voice traits to predict neurological illnesses. Further raising prediction accuracy for PD detection, Lilhore et al. (2023) presented a hybrid CNN-LSTM model with hyperparameter adjustment.

Many gait analysis studies have used gait data to evaluate PD degree and progression. While Gurgenidze et al. (2024) examined wave train electrical activity patterns to evaluate gait freezing in PD patients, Berke et al. (2022) used CNNs for severity prediction utilizing gait characteristics. Furthermore illustrating the possibilities of multimodal techniques, Tunc et al. (2020) investigated speech characteristics for evaluating PD degree using extreme gradient boosting models.

Early diagnosis of EEG data has also benefited from machine learning-based methods like feature selection, genetic algorithms, SVM classifiers. For early PD identification, De Oliveira et al. (2020) used machine learning techniques and EEG data with partial directed coherence. Moreover, research such those by Kamble et al. (2021) and Saeed et al. (2022) have shown how much machine learning improves diagnostic accuracy.

These findings taken together highlight the encouraging role feature engineering, ML, and DL play in early Parkinson's disease diagnosis and progression tracking. These developments in prediction models greatly help to enhance the results of interventions and patient care.

2. BACKGROUND STUDY

Ali, L., et al. (2019) these authors address Parkinson's disease (PD) identification using handwritten data. Considered data was very imbalanced. These authors performed studies to establish data imbalance biases machine learning algorithms. Skewed data-trained machine learning models benefit the dominant class. These authors discovered excellent sensitivity but low specificity for PD diagnosis since the ill class was the majority and the healthy class was the minority. Their random under-sampling method reduced model skewness. The random under-sampling method balanced or optimized training to build unbiased models. PD detection accuracy was improved by combining feature selection with machine learning. This created Chi2-Adaboost, a cascaded learning system. The recommended cascaded learning system outperformed six others. Traditional Adaboost models performed 3.3% better using the cascaded technique.

Anila, M., et al. (2024) as effectively and early diagnose Parkinson's disease using speech features, the LSTM technique seems intriguing. The LSTM model successfully classifies data into PD and non-PD groups by learning complex audio input patterns. The standardized and reliable UCI Parkinson's dataset is used to train and evaluate the LSTM model. The dataset's quantity of speech data from PD patients and healthy controls provides a solid basis for the model. The model's accuracy, precision, recall, and F1 score are used to assess its performance and highlight areas for improvement. The model is highly sought after for fast and accurate PD diagnosis due to its 89.23% accuracy rating. Optimize the model's architecture and hyperparameters, regularize, and terminate early to minimize over-fitting. Overall, the LSTM-based PD detection method is a great tool for early and accurate audio recording PD detection. Early diagnosis and fast intervention enhance Parkinson's disease (PD) treatment and quality of life. More hidden layers and hyper-parameter tweaking with varied values enhance the divergent LSTM-based approach.

Anusri, U., et al. (2021) Parkinson's disease (PD) is a neurological ailment with imprecise prediction, posing problems to the community. their proposed study identifies facial emotions in PD patients and normal individuals, including sadness, happiness, rage, and melancholy. The datasets for this prediction study come from Parkinson's Progression Markers Initiative (PPMI), which includes 188 PD patients and 50 healthy individuals for testing and training. Using this dataset, these authors used Alex Net and Vgg 16 CNN architecture to obtain accuracy, sensitivity, specificity, F1 score, and area under curve. Therefore, Vgg 16 yields 10% more accurate findings than Alex Net. VGG 16 architecture demonstrated 96.5% accuracy, 93% sensitivity, 96% specificity, 97.7% F1 score, and 95.3% area of curve compared to Alex Net research, making it useful for early-stage Parkinson's disease diagnosis in healthcare.

Aydın, F., & Aslan, Z. (2021) these authors described a novel way to detect Parkinson's disease gait patterns. These authors use the vibrations algorithm, a novel ensemble learning method, CART, and HHT, or Hilbert-Huang Transform. HHT, OneRAttributeEval, and sixteen statistical functions were used to carefully design and choose features. The proposed model has a classification accuracy of 98.7879%, TPR of 98.92%, and TNR of 98.61%. Even with contradicting results, their study is more comprehensive and better. These authors found that the heels are a stronger predictor of PD than any other foot-bottom element in persons with and without the disease. These authors also found that left foot signals give more information than right foot signals for categorization and that the L1 signal accounts for 30% of all characteristics. Signal properties such amplitudes (A), maximum extreme values (pks), and peak-height values (p) dominated the selected parameters. Nearly half of the selected variables were based on basic statistical functions like mean, median, and MAD. Hardware implementation is easy with the recommended approach's decreased computational cost. Twenty-four decision tree models were used to create their model. Decision trees generate guidelines.

Chakraborty, S., et al. (2020) Using Ensemble Voting classifiers and Convolutional Neural Networks, this research builds a multistage classification system to identify Parkinson's disease in wave and spiral drawings. Data from spiral and wave

sketches made by both healthy individuals and those with Parkinson's disease were mainly used for categorization in this study. The work's suggested method seems to be rather good at distinguishing between healthy volunteers' drawings and those of Parkinson's sufferers. Averaging 93.3% accuracy, 94% recall, 93.50% precision, and 93.94% f1 score, the model produced the following results for corresponding courses.

Chandra, J., et al. (2021) these authors achieved a very high AUC in differentiating PD patients from controls by discovering intuitive and highly predictive elements in spiral drawings from PD patients. The research shows that this technique has the potential to allow for widespread, point-of-care PD screening, but to rigorously evaluate its accuracy for PD diagnosis; modifications to the drawing task and study design are needed. Tools for screening for PD are crucial for treating PD, especially in underserved regions, due to the rising frequency of the illness and the declining numbers of neurologists globally. Community health care providers and primary care clinics might quickly identify people at risk for PD by creating and verifying low-cost automated handwriting-based screening methods for PD. This would reduce the worldwide burden of PD.

Goyal, J., et al. (2021) nearly 90% of Parkinson's patients have voice issues. Robust feature extraction and categorization help identify PD early on. For oscillatory signals like speech, resonating components reveal persistent oscillations and oscillation transients, unlike time-frequency analysis. Hybrid analysis improves PD diagnosis by integrating the capabilities of both types of analysis. These authors recommend combining resonant component analysis with time-frequency feature extraction. High-resonance components are extracted. PSD is a time-frequency-based characteristic generated by sparsely represented high-resonating components. Components have low or high frequencies. These authors give the CNN classifier PSD pictures to test deep learning's Parkinson's patient classification. These authors achieved 99.37% validation accuracy and 100% training accuracy using a combination of features. The study has also shown the impact of diversity on the workplace to help physicians implement the proposed work in clinical practice. The study found that diversity influences model accuracy. Clinical implementation of the indicated task requires ethnic group data.

Malathi, A., et al. (2024) Using state-of-the-art optimization algorithms and machine learning approaches, these authors presented a thorough framework for PD prediction in this study. These authors conducted experiments to prove that their suggested technique could successfully predict PD from open-source datasets. These authors improved upon previous methods' prediction accuracy by combining feature extraction with ImCfO_Attn_EffBNet and using Empirical Mode Decomposition. Convergence rates and global solution quality were considerably improved with the integration of the ImCfO algorithm. Based on a number of evaluations, the ImCfO_Attn_EffBNet was able to achieve the following results: accuracy (95.068%), recall (92.948%), specificity (92.89%), f-score (92.89%), precision (92.89%), and false positive rate (2.1%). The results show how cutting-edge optimization methods, when combined with state-of-the-art machine learning models, improve healthcare applications and illness prediction.

Table 1: Comparison table on Parkinson's disease

Study	Methodology	Key Features	Performance	Limitations
Saravanan et al. (2023)	Modified deep learning (VGG19-INC) with dynamic learning rates and LIME for explain ability.	Fusion of pre-trained models and dynamically varying rates for improvement.	Superior performance to existing methods.	Requires transfer learning expertise.
Liu et al. (2022)	Radio wave analysis for at-home PD monitoring and progression tracking.	Continuous gait speed measurement; correlation with MDS-UPDRS scores.	Sensitive, objective, and passive assessments.	Data limited to gait-related symptoms.

Soumaya et al. (2021)	Genetic Algorithm with SVM using acoustical and decompositional features of speech.	Feature selection with GA, 10-fold cross-validation.	91.18% accuracy with 15 features.	Limited feature types and non-comparative approaches.
Lamba et al. (2021)	Handwriting analysis using 29 kinematic features with Genetic Algorithm and Mutual Information.	AdaBoost with 96.02% accuracy (9 features); Random Forest with 91.34% accuracy (14 features).	Cannot assess disease severity; specific to handwriting.	Parkinson's but the severity of the disease cannot be diagnosed
Shahid & Singh (2020)	PCA-based DNN for predicting UPDRS scores in PD progression.	Feature extraction using PCA, real-world dataset from UCI.	Outperforms traditional models like MLR, NN.	Performance depends on dataset size.
Moetesum et al. (2019)	CNN-based visual handwriting attributes extraction for PD detection.	Median residual and edge images with raw handwriting images; early and late fusion techniques.	83% accuracy on handwriting dataset.	Focus on offline features only; limited dataset diversity.
Kotsavasiloglou et al. (2017)	NVV metric for motor coordination assessment through simple handwriting tasks.	Normalized Velocity Variability (NVV) as a key feature; touch-sensitive tablet integration.	91% classification accuracy.	Limited to upper limb motor impairments.

3. PROPOSED METHODOLOGY

For the third phase, a holistic approach is adopted by amalgamating data from both wave frequency and spiral drawing image datasets. This phase involves a comprehensive data fusion strategy, amalgamating insights from both modalities to create a more robust and informative dataset. To fortify prediction reliability, **Deep Conformal Neural Networks** are introduced. Trained not only to predict the Parkinson's disease class but also to furnish a confidence score for each prediction, these networks offer a nuanced understanding of prediction reliability, contributing to heightened transparency and interpretability in Parkinson's disease diagnosis.

3.1 Dataset

Based on voice recordings and different speech characteristics, this dataset has information capable of detecting Parkinson's disease (PD). Classification problems, in which the aim is to separate patients with Parkinson's disease from healthy people, often employ the dataset. Extracted from voice recordings, the main characteristics of the dataset center on acoustic aspects influenced by the condition.

Frequency Dataset 1: https://www.kaggle.com/datasets/naveenkumar20bps1137/parkinsons-disease-detection

This collection seems to be centered on image-based information linked with Parkinson's disease. Based on the description, photos probably medical scans or images from diagnostic tests relevant to Parkinson's Disease diagnosis or analysis appear to abound.

Image Dataset 2: https://data.mendeley.com/datasets/fd5wd6wmdj/1

3.2 Deep Conformal Neural Networks

Inspired by biological neural networks in human brain processes, Artificial Neural Networks (ANN) are a computational method used in order to address prediction issues in computer vision, data mining, etc. Artificial neural networks are the theoretical roots of Deep Conformal Neural Networks (DCNN) topology. General deep framework for classification or regression analysis, DCNN is a very common learning method producing effective results by inferring from a dataset. Various topologies have been explored by means of distinct deep learning algorithms and methods. For a long period, it will remain quite popular in computer science and other multi-disciplined fields. Deep neural networks are a potent tool in machine learning research including pattern recognition and natural language processing when compared with other conventional learning approaches.

$Z_{i,j,k} = \sum_{m=1}^{h} \sum_{n=1}^{w} \sum_{c=1}^{C} W_{m,n,c,k} \cdot X_{i+m-1,j+n-1,c} + b_k$ ---------- (1)

This formula represents a key operation in a Deep Conformal Neural Network (DCNN). It describes the computation of the output feature map $Z_{i,j,k}$ at position (i,j) for the $k-th$ filter by performing a convolution between the input X and the weight kernel W. The triple summation iterates over the height h, width www, and channels C of the filter, while b_k is the bias term added after the convolution operation. This process essentially aggregates the contributions from different parts of the input to produce the final output feature.

$A_{i,j,k} = \max(0, Z_{i,j,k})$ ---------- (2)

This formula represents the Rectified Linear Unit (ReLU) activation function applied to the output $Z_{i,j,k}$ from the previous convolution operation. It sets any negative values in $Z_{i,j,k}$to zero while keeping positive values unchanged. Essentially, $A_{i,j,k}$is the activated output, where the ReLU function introduces non-linearity by allowing only non-negative values to pass through, helping the network learn more complex patterns.

$P_{i,j,k} = \max\{A_{m,n,k}\}, m \in [i: i+p_h], n \in [i: i+p_w]$ ---------- (3)

This formula describes the max pooling operation, where $P_{i,j,k}$ is the pooled value at position (i,j) for the $k-th$ feature map. The operation involves taking the maximum value from a local region of size $p_h \times p_w$ centered on (i,j) in the input feature map A. The indices m and n specify the window of values over which the maximum is computed, effectively down-sampling the input while retaining the most important features for the next layer.

$P_{i,j,k} = \frac{1}{p_h \cdot p_w} \sum_{m=i}^{i+p_h} \sum_{n=j}^{j+p_w} A_{m,n,k}$ ---------- (4)

This formula represents the average pooling operation, where $P_{i,j,k}$ is the average value in a local region of size $p_h \times p_w$from the input feature map A. It calculates the average of all values within the pooling window, effectively down-sampling the input while preserving the overall features in a less sensitive way than max pooling.

$Z^{[l]} = W^{[l]} A^{[l-1]} + b^{[l]}$ ---------- (5)

$A^{[l]} = \sigma(Z^{[l]})$ ---------- (6)

The formula (5) represents the linear transformation applied to the input from the previous layer$A^{[l-1]}$. It involves multiplying the input by the weight matrix$W^{[l]}$, followed by adding the bias term $b^{[l]}$, resulting in the pre-activation values $Z^{[l]}$ for the current layer.

The formula (6) applies a non-linear activation function σ (such as ReLU, sigmoid, or tanh) to the pre-activation values $Z^{[l]}$, producing the activated output $A^{[l]}$ for the current layer, which is then passed to the next layer.

$\hat{y}_k = \frac{e^{Z_k}}{\sum_{j=1}^{n_y} e^{Z_j}}$ ---------- (7)

$\hat{y} = \frac{1}{1+e^{-Z}}$ ---------- (8)

The formula (7) is the softmax function, commonly used for multi-class classification. It converts the raw scores $(logits)$ Z_k for each class into probabilities by exponentiating each score, normalizing it by the sum of exponentiated scores, ensuring that the output is a probability distribution across all classes.

The formula (8) is the sigmoid function, used for binary classification. It maps the raw score Z into a probability between 0 and 1, indicating the likelihood of the positive class. The output $\hat{y}$ represents the probability of the positive class, with values closer to 1 indicating a higher probability.

$L = -\frac{1}{m} \sum_{i=1}^{m} \sum_{k=1}^{n_y} y_k{}^{(i)} log\,(\hat{y}_k{}^{(i)})$ ---------- (9)

$L = \frac{1}{m} \sum_{i=1}^{m} (y^{(i)} - \hat{y}^{(i)})^2$ ---------- (10)

The formula (9) is the cross-entropy loss used for multi-class classification problems. It measures the difference between the true class labels ${y_k}^{(i)}$ and the predicted probabilities ${\hat{y}_k}^{(i)}$. The loss is averaged over all m training examples, penalizing the model more when its predictions deviate from the true labels.

The formula (10) is the Mean Squared Error (MSE) loss, typically used for regression tasks. It computes the squared differences between the true values $y^{(i)}$and the predicted values$\hat{y}^{(i)}$, averaging them over all training examples to quantify how far the model's predictions are from the actual values.

$W \coloneqq W - \alpha \cdot \frac{\partial L}{\partial W}, b \coloneqq b - \alpha \cdot \frac{\partial L}{\partial b}$ ---------- (11)

The formula (11) updates the weights W and biases b by subtracting a fraction of the gradients of the loss function L with respect to each parameter. Here, α is the learning rate, which controls the step size of each update. The goal is to minimize the loss function by iteratively adjusting the weights and biases in the direction that reduces the error.

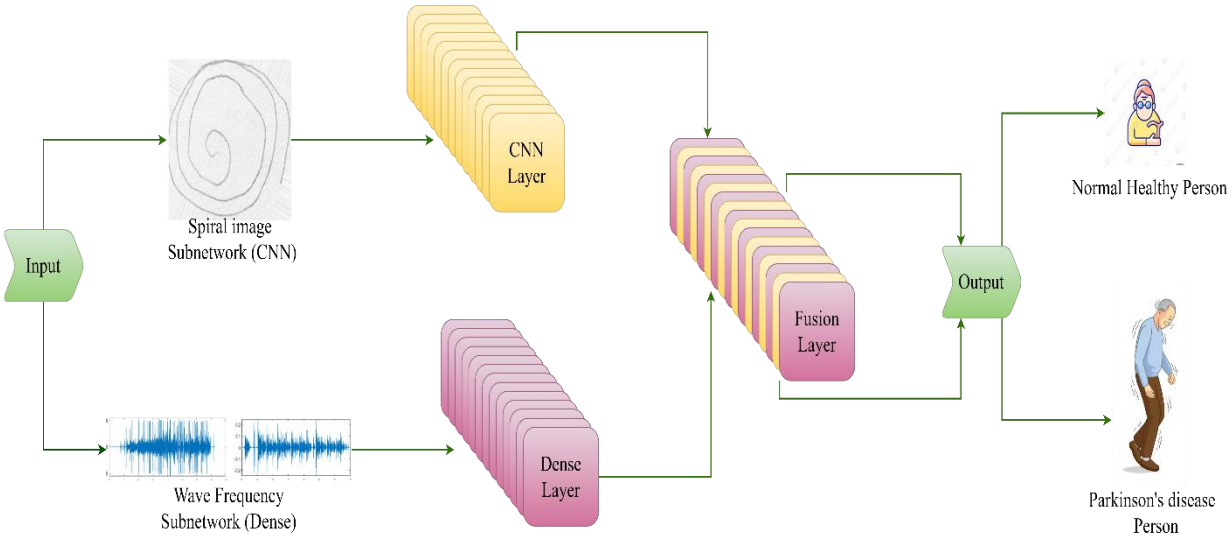

Figure 1: Architecture of Deep Conformal Neural Networks

In this figure 1 spiral image and wave frequency is the input. These two are undergo in CNN and Dense process and it will send to the fusion layer of DCNN. After the fusion layer the data gives the output as the person is a normal healthy person or Parkinson's disease affected person.

Algorithm: Deep Conformal Neural Networks

Input: Image and Wave Frequency

Output: Either Normal or Parkinson's disease

Initialize $cand\_set = \{\emptyset\}$

If node i receives PD message from node j then

$cand\_set = cand\_set \cup \{j\}$

End if

Node j in $cand\_set\ such\ that\ (j) \exists if\ \&\&\ ts(j) > 1\ then\ //\ ts$ is the time slot

$PD(i) = PD(j) + 1$

$ts(i) = ts(j) - 1$

Else node j in $cand\_set$ such that $|N(j)| \exists if\ < ts(j)\ then$

$PD(i) = PD(j) + 1$

$//\ f\ is\ the\ free\ time\ slot$

$ts(i) = f, f \in \{1, 2, \dots, j-1\}\ such\ that\ ts(i) \neq ts(k), \forall\ k \in N(j) \&\& PD(k)$

$= PD(j) + 1$

Else

$UPDATE\_SCH(i, cand\_set)$

End if

End if

The DCNN algorithm uses the picture and wave frequency datasets to produce a Parkinson's disease (PD) diagnosis. The algorithm's architecture is intended to refresh the collection of candidate nodes and employ temporal slots for prediction updates, eventually diagnosing Parkinson's disease by combining insights from both modalities (images and audio). The "Flow Chart of Deep Conformal Neural Networks" depicts the network's systematic method for node updates and temporal scheduling.

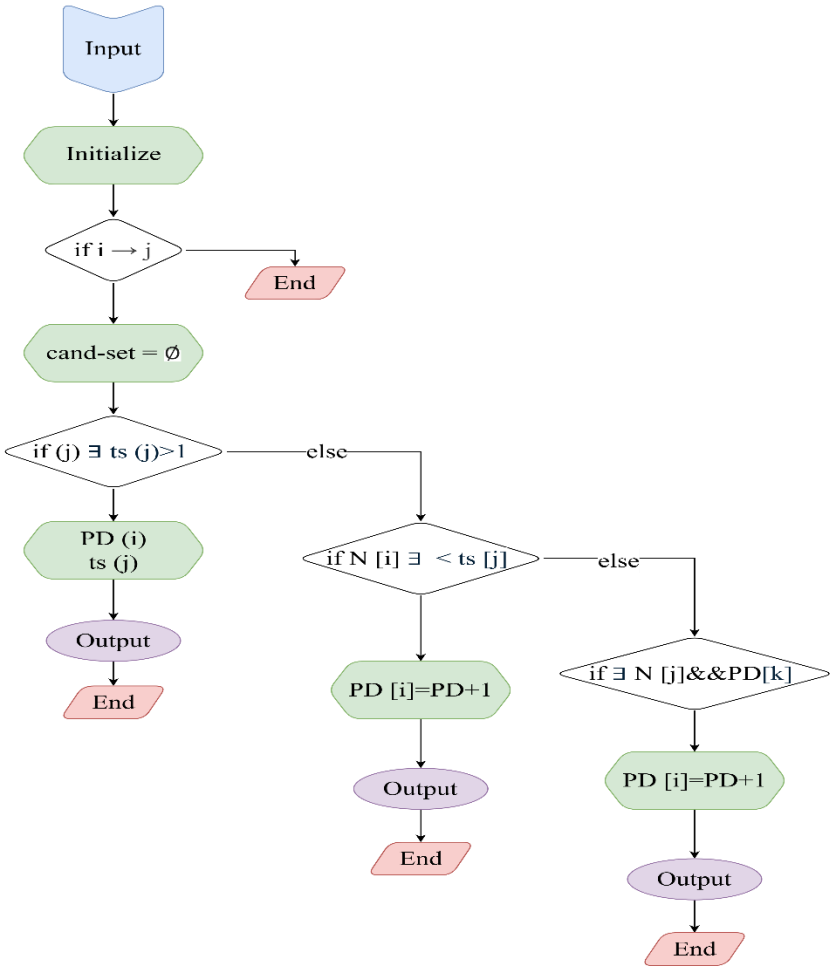

Figure 2: Flow Chart of Deep Conformal Neural Networks

Designed for categorization challenges like Parkinson's illness, Deep Conformal Neural Networks (DCNN) has architecture shown in this Figure 2. It starts with inputs such photos and wave frequency data then works them through many layers of convolution and activation functions. To lower dimensionality and emphasize the most important characteristics, the model uses pooling both max and average retinues. The last output layer sorts the input as either normal or suggesting Parkinson's illness using softmax or sigmoid. Gradient descent helps the model's parameters weights and biases to be improved, hence reducing the prediction error.

4. RESULTS AND DISCUSSION

The proposed method has implemented by using python programming with the use of two different dataset like spiral drawings and wave frequency from EEG recordings. This result shows that the proposed methodology gives best performance comparing to the existing methodology.

4.1 Accuracy

In predictive modeling, accuracy is the measure of how close the model's projections are to real-world outcomes. Making predictions and judgments in a variety of circumstances relies on the model's reliability and accuracy, thus it assesses these

characteristics.

T-True, F-False, P-Positive, N-Negative

$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ -------- (12)

4.2 Precision

In predictive modeling, accuracy is the proportion of total expected positive observations to correctly forecasted positive observations. It displays how effectively the model lowers false positives, ensuring the genuine accuracy and reliability of the positive predictions it generates qualities necessary for decision-making and, as a result, error reduction in many other domains.

$Precision = \frac{TP}{TP+FP}$ ------ (13)

4.3 Recall

Recall in predictive modeling is the fraction of real positive instances the model properly detected. In sectors like as medical diagnosis or fraud detection, identifying all positives is critical since it shows how well the model detects all relevant instances of a particular class.

$Recall = \frac{TP}{TP+FN}$ ------ (14)

4.4 F-measure

The F-measure, which determines the harmonic mean of recall and accuracy, is a strong all-around measurement of how well a model is performing for models that need to prevent both false positives and false negatives.

$F - measure = 2 \times \frac{Precision \times recall}{precision+recall}$ ------- (15)

Table 2: Comparison table on Performance Metrics

Algorithms	Accuracy	Precision	Recall	F-measure
CNN	93	92	93	90
YOLO-V4	94	93	94	91
VGG-16	95	94	95	92
VGG-19	96	95	96	93
Resnet-50	97	96	97	94
Resnet-150	98	97	98	95
Deep Conformal Neural Networks	99	98	99	96

Table 2 compares the performance of several neural network algorithms using four essential metrics: accuracy, precision, recall, and F-measure. These metrics measure how effectively models perform in tasks like as categorization. As the models develop from CNN to Resnet-150, the numbers for each measure rise, indicating improved overall performance. The Deep Conformal Neural Networks model achieved the greatest scores: 99% accuracy, 98% precision, 99% recall, and 96% F-measure. This shows that this model excels at properly identifying things, reducing mistakes, and striking a balance between accuracy and recall, making it very trustworthy for its intended use.

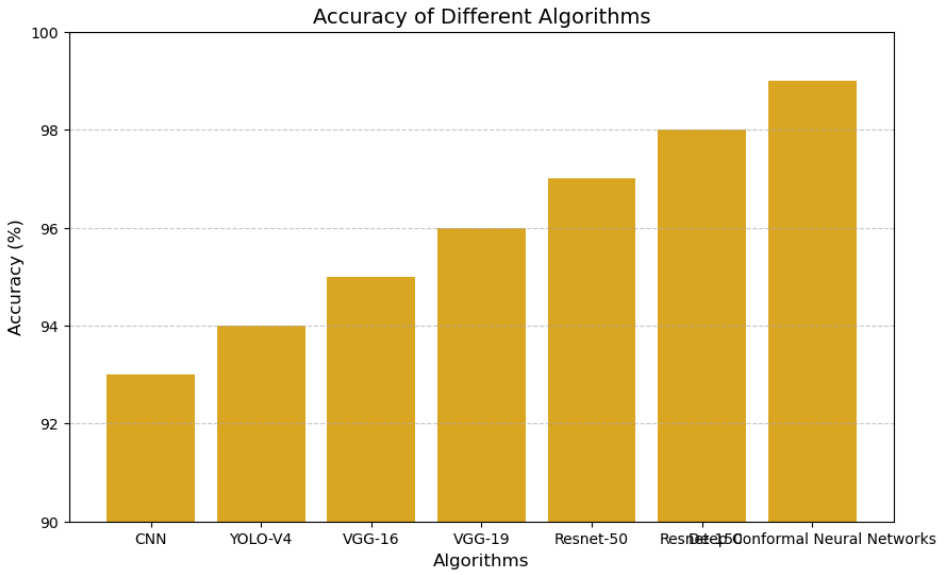

Figure 3: Comparison chart on Accuracy

This Figure 3 compares the efficacy of several ML methods, with algorithm names on the x-axis and percentages representing their relative accuracies. Beginning with "CNN" and progressing to "Deep Conformal Neural Networks," the algorithms are organized in a manner that reflects their escalating level of accuracy. The y-axis has gridlines to make reading the values easier, and it can be adjusted to center the 90-100% range. The superiority of the "Deep Conformal Neural Networks" over the others is shown by their 99% accuracy rate.

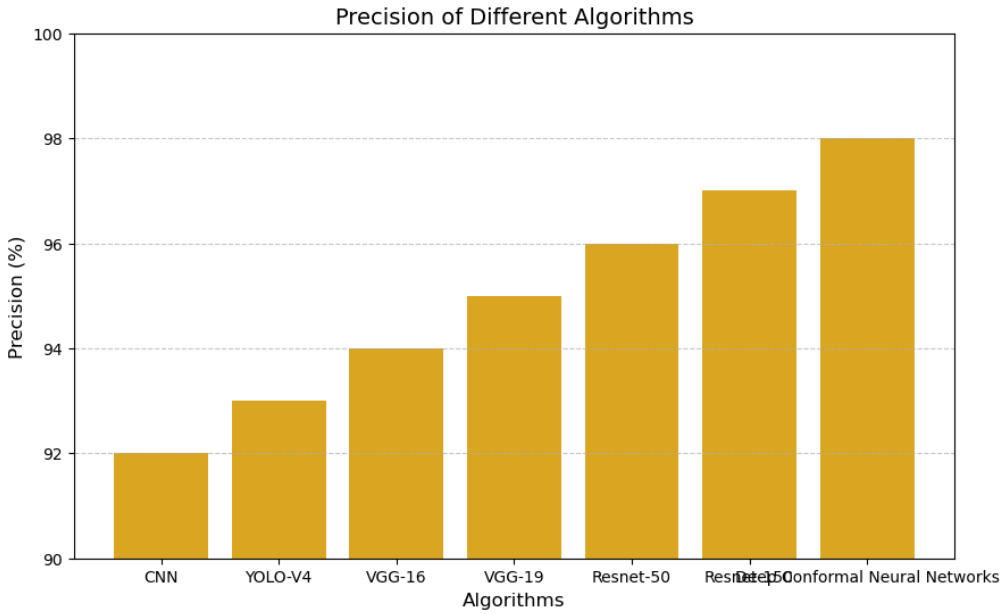

Figure 4: Comparison chart on Precision

This Figure 4 compares the efficacy of several ML methods, with algorithm names on the x-axis and percentages representing their relative Precision. Beginning with "CNN" and progressing to "Deep Conformal Neural Networks," the algorithms are organized in a manner that reflects their escalating level of Precision. The y-axis has gridlines to make reading the values easier, and it can be adjusted to center the 90-100% range. The superiority of the "Deep Conformal Neural Networks" over the others is shown by their 98% Precision rate.

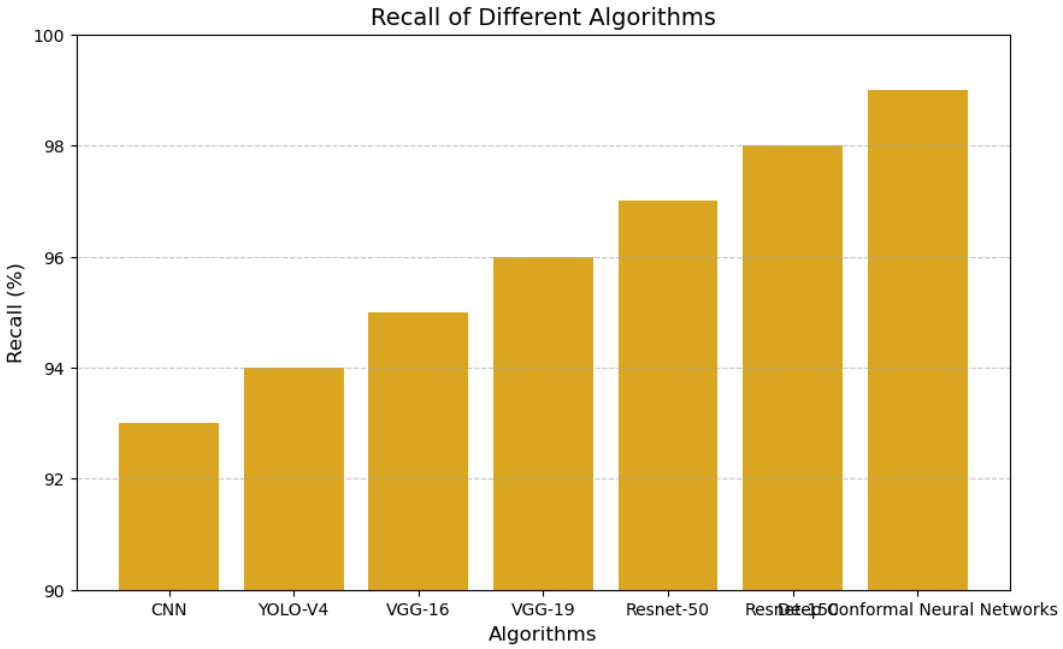

Figure 5: Comparison chart on Recall

This Figure 5 compares the efficacy of several ML methods, with algorithm names on the x-axis and percentages representing their relative Recall. Beginning with "CNN" and progressing to "Deep Conformal Neural Networks," the algorithms are organized in a manner that reflects their escalating level of Recall. The y-axis has gridlines to make reading the values easier, and it can be adjusted to center the 90-100% range. The superiority of the "Deep Conformal Neural Networks" over the others is shown by their 99% Recall rate.

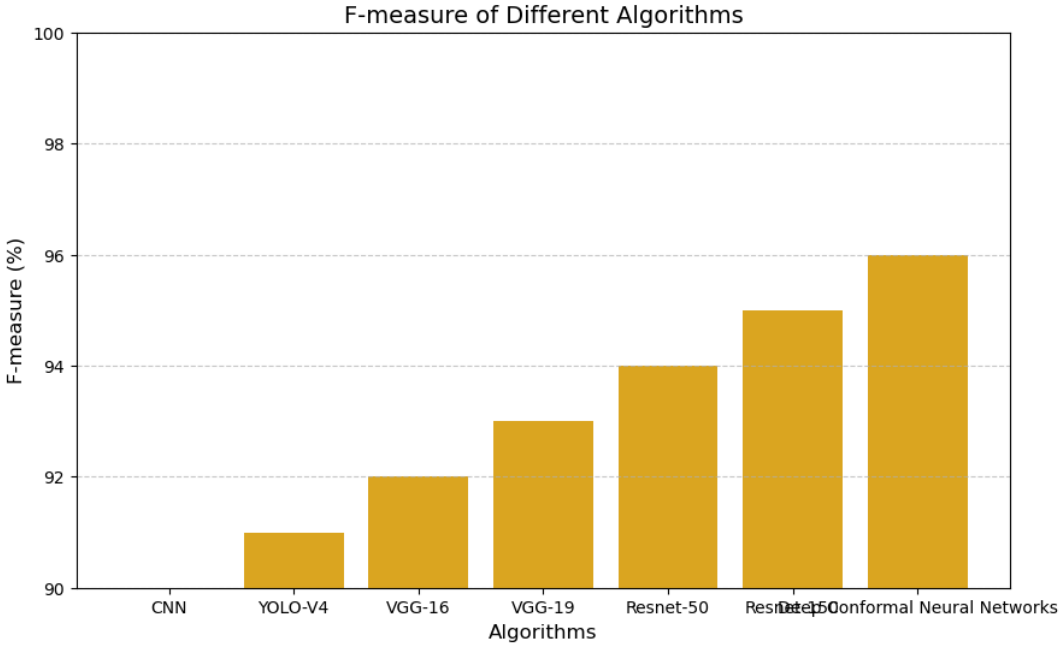

Figure 6: Comparison chart on F-measure

This Figure 6 compares the efficacy of several ML methods, with algorithm names on the x-axis and percentages representing their relative F-measure. Beginning with "CNN" and progressing to "Deep Conformal Neural Networks," the algorithms are organized in a manner that reflects their escalating level of F-measure. The y-axis has gridlines to make reading the values easier, and it can be adjusted to center the 90-100% range. The superiority of the "Deep Conformal Neural Networks" over the others is shown by their 96% F-measure rate.

5. CONCLUSION

In conclusion, the study demonstrates that Deep Conformal Neural Networks (DCNN), when combined with conventional machine learning techniques, offer significant improvements in the identification of Parkinson's disease. Among the models tested, DCNN achieved the highest performance, with an impressive 99% accuracy, alongside 98% recall and 96% F-measure, highlighting its ability to generate accurate predictions and effectively identify true positives. This performance not only ensures minimal missed diagnoses but also reduces false positives, which is critical in clinical applications. The fusion of image-based data and wave frequency datasets within the DCNN framework enhances its predictive power, making it particularly well-suited for the early detection of Parkinson's disease. This multi-modal data approach improves both the precision and reliability of the model's predictions, ensuring more accurate clinical decisions. Furthermore, the inclusion of a confidence score system within the DCNN enhances interpretability, providing greater transparency and facilitating clinical decision-making. Overall, the findings highlight the potential of DCNN as a powerful tool for improving Parkinson's disease diagnosis. The combination of high accuracy, strong recall, and enhanced interpretability creates a robust system that offers both clinical reliability and transparency. This work underscores the growing role of advanced deep learning models in transforming medical diagnostics, particularly in the context of complex and early-stage diseases like Parkinson's. With continued research and refinement, DCNN could become a vital asset in enhancing diagnostic processes and patient care.

REFERENCES

[1] Ali, L., Zhu, C., Golilarz, N. A., Javeed, A., Zhou, M., & Liu, Y. (2019). Reliable Parkinson's disease detection by analyzing handwritten drawings: construction of an unbiased cascaded learning system based on feature selection and adaptive boosting model. *Ieee Access*, *7*, 116480-116489.

[2] Anila, M., Kumar, G. K., Rani, D. M., Kantipudi, M. P., & Jayaram, D. (2024). An LSTM based DNN Model for Neurological Disease Prediction Using Voice Characteristics. *EAI Endorsed Transactions on Pervasive Health and Technology*, *10*.

[3] Anusri, U., Dhatchayani, G., Angelinal, Y. P., & Kamalraj, S. (2021, June). An early prediction of Parkinson's disease using facial emotional recognition. In *Journal of Physics: Conference Series* (Vol. 1937, No. 1, p. 012058). IOP Publishing.

[4] Aydın, F., & Aslan, Z. (2021). Recognizing Parkinson's disease gait patterns by vibes algorithm and Hilbert-Huang transform. *Engineering Science and Technology, an International Journal*, *24*(1), 112-125.

[5] Berke Erdaş, Ç., Sümer, E., & Kibaroğlu, S. (2022). CNN-based severity prediction of neurodegenerative diseases using gait data. *Digital Health*, *8*, 20552076221075147.

[6] Chakraborty, S., Aich, S., Han, E., Park, J., & Kim, H. C. (2020, February). Parkinson's disease detection from spiral and wave drawings using convolutional neural networks: A multistage classifier approach. In *2020 22nd International Conference on Advanced Communication Technology (ICACT)* (pp. 298-303). IEEE.

[7] Chandra, J., Muthupalaniappan, S., Shang, Z., Deng, R., Lin, R., Tolkova, I., ... & Press, D. Z. (2021). Screening of Parkinson's disease using geometric features extracted from spiral drawings. *Brain Sciences*, *11*(10), 1297.

[8] De Oliveira, A. P. S., De Santana, M. A., Andrade, M. K. S., Gomes, J. C., Rodrigues, M. C., & dos Santos, W. P. (2020). Early diagnosis of Parkinson's disease using EEG, machine learning and partial directed coherence. *Research on Biomedical Engineering*, *36*, 311-331.

[9] Goyal, J., Khandnor, P., & Aseri, T. C. (2021). A hybrid approach for Parkinson's disease diagnosis with resonance and time-frequency based features from speech signals. *Expert Systems with Applications*, *182*, 115283.

[10] Gurgenidze, A. V., Sushkova, O. S., Khokhlova, M. N., & Morozov, A. A. (2024, May). Investigating Parkinson's Disease Gait Freezing Through the Analysis of Wave Train Electrical Activity Patterns. In *2024 X International Conference on Information Technology and Nanotechnology (ITNT)* (pp. 1-5). IEEE.

[11] Handojoseno, A. A., Shine, J. M., Nguyen, T. N., Tran, Y., Lewis, S. J., & Nguyen, H. T. (2013, July). Using EEG spatial correlation, cross frequency energy, and wavelet coefficients for the prediction of Freezing of Gait in Parkinson's Disease patients. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 4263-4266). IEEE.

[12] Kamble, M., Shrivastava, P., & Jain, M. (2021). Digitized spiral drawing classification for Parkinson's disease diagnosis. *Measurement: Sensors*, *16*, 100047.

[13] Kamoji, S., Koshti, D., Dmello, V. V., Kudel, A. A., & Vaz, N. R. (2021, July). Prediction of Parkinson's Disease using Machine Learning and Deep Transfer Learning from different Feature Sets. In *2021 6th International Conference on Communication and Electronics Systems (ICCES)* (pp. 1715-1720). IEEE.

[14] Karan, B., Sahu, S. S., & Mahto, K. (2020). Parkinson disease prediction using intrinsic mode function based

features from speech signal. *Biocybernetics and Biomedical Engineering*, *40*(1), 249-264.

[15] Kotsavasiloglou, C., Kostikis, N., Hristu-Varsakelis, D., & Arnaoutoglou, M. (2017). Machine learning-based classification of simple drawing movements in Parkinson's disease. *Biomedical Signal Processing and Control*, *31*, 174-180.

[16] Kurmi, A., Biswas, S., Sen, S., Sinitca, A., Kaplun, D., & Sarkar, R. (2022). An ensemble of CNN models for Parkinson's disease detection using DaTscan images. *Diagnostics*, *12*(5), 1173.

[17] Lamba, R., Gulati, T., Al-Dhlan, K. A., & Jain, A. (2021). A systematic approach to diagnose Parkinson's disease through kinematic features extracted from handwritten drawings. *Journal of Reliable Intelligent Environments*, 1-10.

[18] Lilhore, U. K., Dalal, S., Faujdar, N., Margala, M., Chakrabarti, P., Chakrabarti, T., ... & Velmurugan, H. (2023). Hybrid CNN-LSTM model with efficient hyperparameter tuning for prediction of Parkinson's disease. *Scientific Reports*, *13*(1), 14605.

[19] Liu, Y., Zhang, G., Tarolli, C. G., Hristov, R., Jensen-Roberts, S., Waddell, E. M., ... & Katabi, D. (2022). Monitoring gait at home with radio waves in Parkinson's disease: A marker of severity, progression, and medication response. *Science Translational Medicine*, *14*(663), eadc9669.

[20] Malathi, A., Ramalakshmi, R., Gandhi, V., & Bhuvanesh, A. (2024). Parkinson disease prediction using improved crayfish optimization based hybrid deep learning. *Technology and Health Care*, 09287329241296352.

[21] Moetesum, M., Siddiqi, I., Vincent, N., & Cloppet, F. (2019). Assessing visual attributes of handwriting for prediction of neurological disorders—A case study on Parkinson's disease. *Pattern Recognition Letters*, *121*, 19-27.

[22] Saeed, F., Al-Sarem, M., Al-Mohaimeed, M., Emara, A., Boulila, W., Alasli, M., & Ghabban, F. (2022). Enhancing Parkinson's disease prediction using machine learning and feature selection methods. *Computers, Materials and Continua*, *71*(3), 5639-5658.

[23] Salmanpour, M. R., Shamsaei, M., Saberi, A., Klyuzhin, I. S., Tang, J., Sossi, V., & Rahmim, A. (2020). Machine learning methods for optimal prediction of motor outcome in Parkinson's disease. *Physica Medica*, *69*, 233-240.

[24] Saravanan, S., Ramkumar, K., Narasimhan, K., Subramaniyaswamy, V., Kotecha, K., & Abraham, A. (2023). Explainable Artificial Intelligence (EXAI) models for early prediction of Parkinson's Disease based on spiral and Wave drawings. *IEEE Access*.

[25] Shahid, A. H., & Singh, M. P. (2020). A deep learning approach for prediction of Parkinson's disease progression. *Biomedical Engineering Letters*, *10*, 227-239.

[26] Soumaya, Z., Taoufiq, B. D., Benayad, N., Yunus, K., & Abdelkrim, A. (2021). The detection of Parkinson disease using the genetic algorithm and SVM classifier. *Applied Acoustics*, *171*, 107528.

[27] Tunc, H. C., Sakar, C. O., Apaydin, H., Serbes, G., Gunduz, A., Tutuncu, M., & Gurgen, F. (2020). Estimation of Parkinson's disease severity using speech features and extreme gradient boosting. *Medical & Biological Engineering & Computing*, *58*, 2757-2773.