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A Review on Parkinson's Disease Detection Using Spiral Drawings and MRI Images

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Abstract: ***Parkinson's Disease (PD) is a progressive neurode generative disorder that affects millions globally, often going undiagnosed until motor symptoms become severe. Early and ac curate detection is essential for effective treatment and improved quality of life. In this study, we describe the use of Convolutional Neural Networks (CNNs) to recognize and classify Parkinson's Disease using two key modalities: spiral drawings and MRI brain images. From 20 recent research papers, we present a com prehensive review of CNN-based approaches for PD detection, highlighting their advantages over traditional diagnostic methods. We introduce the basic concepts of CNNs and emphasize their ability to extract motor and structural features directly from raw images, outperforming manual scoring and conventional machine learning techniques.By combining motor and structural biomarkers, CNN-based systems offer a powerful tool for early PD detection. The fusion of spiral drawings and MRI images not only improves diagnostic accuracy but also supports neurologists in clinical decision-making. The use of AI in Parkinson's Disease detection has the potential to transform healthcare delivery by enabling scalable, cost-effective, and patient-friendly solutions. CNN, ResNet-50, VGG-16, DenseNet, Spiral Drawing, MRI, Parkinson's Disease, Deep Learning, Transfer Learning, Feder ated Learning, Mobile Diagnosis.***

Keywords: CNN, ResNet-50, VGG-16, DenseNet, Spiral Drawing, MRI, Parkinson's Disease, Deep Learning, Transfer Learning

I. INTRODUCTION

Parkinson's Disease (PD) is a progressive neurodegener ative disorder that primarily affects motor function, leading to symptoms such as tremors, rigidity and bradykinesia. It also impacts cognitive and emotional health, making early diagnosis essential for effective intervention and improved quality of life [1].Traditional diagnostic methods rely heavily on clinical observation and neurological scoring systems. These approaches, while widely used, often suffer from subjectivity and delayed detection, especially in the early stages of PD [3]. To overcome these limitations, researchers have turned to non invasive, data driven techniques that can detect subtle motor and neurological changes more reliably.Spiral and wave drawings have emerged as valuable tools for assessing f ine motor control. These simple tasks when digitized reveal patterns of tremor, instability and pressure variation that are indicative of PD [5]. Studies have shown that convolutional neural networks (CNNs) can automatically extract meaningful features from these drawings, improving classification accu racy and reducing reliance on manual feature engineering [6].In parallel, magnetic resonance imaging (MRI) has become a critical modality for analyzing structural and functional brain changes associated with PD. T1 weighted and FLAIR sequences, in particular, help differentiate PD from other parkinsonian syndromes by highlighting affected regions such as the substantia nigra and basal ganglia [7]. Deep learning models like DenseNet and ResNet have demonstrated strong performance in MRI based PD classification tasks [13].

Recent research has explored hybrid architectures that combine CNNs with Long Short-Term Memory (LSTM) networks to capture both spatial and temporal patterns in MRI sequences. These models have achieved high diagnostic accuracy and improved generalization across datasets [9]. Lightweight networks such as MobileNet and SqueezeNet have also been adopted for mobile deployment, enabling real time screening in remote or resource limited settings [12].To further enhance performance, some studies integrate geometric features such as area, perimeter, and curvature extracted from spiral drawings with deep learning outputs. This fusion of handcrafted and learned features has led to more robust and interpretable models [19]. Ensemble classifiers like Random Forest and CatBoost have also been used to refine predictions and reduce false positives[20]. Despite these advances, challenges remain. Many models are trained on small datasets, limiting their generalizability. Variations in drawing tools, image quality, and MRI protocols can affect performance. Moreover, the lack of explainability in deep learning models poses barriers to clinical adoption [10]. To address these issues, researchers are incorporating data augmentation, normalization and explainable AI (XAI) techniques to improve transparency and trust[16].This survey paper reviews twenty recent studies on PD detection using spiral drawings and MRI images.

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It compares methodologies, model architectures, preprocessing techniques, and evaluation metrics. The goal is to identify best practices and future directions for building scalable, interpretable, and clinically viable PD screening systems. These insights will also inform the design of our proposed system, which integrates spiral and MRI data using a dual-CNN pipeline with feature fusion and lightweight deployment capabilities.

II. LITERATURE SURVEY

The development of automated, objective diagnostic tools for neurodegenerative disorders has been significantly ac celerated by advances in machine learning, with a primary focus on detecting Parkinson's Disease (PD) through the analysis of subtle motor indicators and neuroimaging data. A particularly innovative and high-performing approach was introduced in the paper "Parkinson's Disease Prediction With Spiral Drawings and Wave Frequency Using Deep Conformal Neural Networks" by SasiRekha et al. [1], who pioneered a truly multimodal method. They ingeniously merged spiral drawing images, which capture fine motor control, with wave frequency data derived from EEG recordings, which reflect neural oscillatory patterns. This fusion created a single, robust dataset for a Deep Conformal Neural Network (DCNN), an architecture designed not only to classify but also to quantify the confidence of its predictions. This dual output is crucial for clinical trust, as it provides a measure of certainty alongside the diagnosis. Their model achieved an outstanding 99% accuracy, 98% precision, 99% recall, and a 96% F-measure. This focus on high performance through multimodal data is echoed in other studies; for instance, in "Deep Learning Approach for Parkinson's Screening with Geometric Features from Spiral and Wave Drawings," Malik et al. [19] combined a rich set of geometric features such as area, perimeter, eccentricity, compactness and curvature extracted from spiral and wave drawings with advanced CNN models like VGG-16 and ResNet-50. Their images were f irst meticulously processed using techniques like grayscale conversion, sharpening, thresholding, erosion, and dilation to enhance quality, leading to remarkable accuracies between 97-98%. Similarly, in their work "Early Parkinson's Disease Diagnosis through Hand-Drawn Spiral and Wave Analysis Using Deep Learning Techniques," Huang et al. [11] employed a deep transfer learning framework on the NIATS dataset, testing six state-of-the-art models and using advanced data augmentation techniques like AugMix and PixMix to improve model robustness and reduce overfitting, along with a cosine annealing scheduler to dynamically adjust the learning rate for optimal convergence, finding that a VGG19 model achieved 96.67% accuracy.

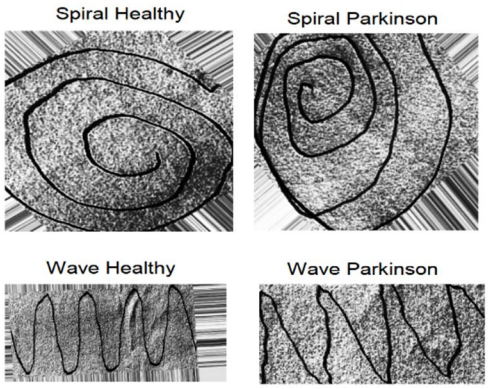


Fig. 1 Histogram equalized and augmented spiral and wave sketches from healthy and Parkinson's patients(adapted from[17])

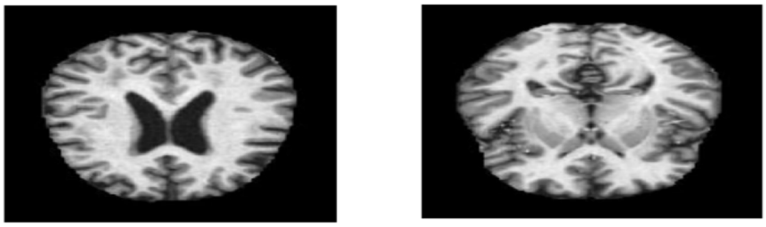
The success of deep learning in this domain is often attributed to its ability to automatically learn discriminative features, a capability powerfully demonstrated by transfer learning models. This approach is particularly vital for medical imaging, where large, annotated datasets are often scarce. Transfer learning leverages knowledge from models pre trained on massive, general-purpose datasets like ImageNet, which have already learned to recognize fundamental features like edges, textures, and shapes. Farhah [6] evaluated several such pre-trained models on a dataset of 102 spiral images, f inding that InceptionV3, after fine-tuning, achieved 89% accuracy with a high ROC value of 95%. Similarly, Aldhyani et al. [3] applied this strategy using DenseNet201 and VGG16 on a dataset of 204 spiral and wave images. The pre-trained CNNs automatically focused on extracting motor irregular ities in the drawings such as shakiness, uneven pressure, and micrographia that are characteristic of PD tremors, with DenseNet201 reaching 94% accuracy and a 99 ROC for spiral images. These studies highlight how this strategy circumvents the need to train a deep network from scratch, significantly boosting performance on specialized medical tasks and making state-of-the-art diagnostics more accessible.

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Beyond transfer learning, custom-designed CNN architec tures have also shown considerable promise, tailored specifi cally to the nuances of PD-related motor patterns. Alniemi and Mahmood [15] designed a detailed sixteen-layer CNN, which included three convolutional layers using batch normalization to stabilize learning and ReLU activation to introduce non linearity, followed by max-pooling layers to downsample and create spatial invariance, and a fully connected layer end ing in a softmax classifier. After preprocessing the images by converting them to grayscale and resizing to 256x256 pixels, their model achieved 93.33% accuracy, 100% recall, and a 93.75% F-measure. In a system-level integration that bridges the gap between research and application, Ramya et al. [14] combined a CNN with an SVM classifier to reach 93% accuracy. Their study used a dataset of 102 drawings that underwent preprocessing steps such as flipping, rotation, and shearing to improve the model's ability to handle data variations. They took the crucial additional step of integrating their model into a React-based application, demonstrating a clear path towards real-world telemedicine deployment, where clinicians could potentially receive real-time predictions and ongoing monitoring for their patients.

As the field matures, researchers are building increas ingly sophisticated systems that move beyond single-model approaches, drawing inspiration from the collaborative nature of human expert diagnosis. Multistage and ensemble systems have proven effective, as seen in the work of Chakraborty et al. [17], who used two separate CNNs to analyze spiral and wave images independently, allowing each model to become a specialist in its domain. After preprocessing the images with resizing, histogram equalization to improve contrast, and augmentation to increase diversity, their prediction probabili ties were combined via ensemble voting with meta-classifiers like Logistic Regression and Random Forest. This "wisdom of the crowd" approach achieved a robust 93.3% accuracy and an average F1-score of 93.94%, often leading to more generalized and reliable performance than any single model could achieve. Similarly, Huang et al. [11] achieved their high 96.67% accuracy with a VGG19 model by combining advanced augmentation with a dynamic learning rate, show casing the importance of sophisticated training strategies that go beyond just model architecture. The scope of motor task analysis is also expanding beyond simple spirals to include more complex and revealing tasks that challenge a wider range of motor skills. Alissa et al. [18] introduced a method for PD diagnosis based on analyz ing patient movements during figure copying tasks like the wire cube and Archimedean spiral pentagon, which require more complex planning and execution. They transformed the multidimensional time series data from a pressure sensitive tablet including coordinates, pressure, and pen angles into 2D grayscale images representing pressure and spatial informa tion. This creative data transformation allows CNNs to be applied to complex temporal data, encoding both spatial and temporal information into a single image format. Trained and validated using ten-fold cross validation, their CNN achieved 93.53% accuracy and a Kappa of 0.87. In a foundational study, Gil-Mart´ ınez et al. [16] used a similar transformation strategy, converting the time series data of spiral drawing coordinates (X, Y, Z, pressure, grip angle) into a 2D Fast Fourier Transform (FFT) matrix. By specifically looking at the frequency range between 0 and 25 Hz, their model focused on the spectral signatures of PD tremors and dyskinesia, achieving 96.5% accuracy and an AUC of 99.2% and establishing a strong precedent for spectral analysis in PD detection.

Despite the dominance of deep learning, traditional ma chine learning methods with carefully engineered features remain highly competitive and offer valuable, often more interpretable, insights into the biomechanics of PD. Agarwal et al. [5] directly compared a traditional approach with a deep learning one on a public dataset of 55 spiral drawings. They found that a Random Forest classifier using Histogram of Oriented Gradients (HOG) features, which capture the distribution of edge directions within an image, outperformed an image-enhancement CNN, achieving 86.67% accuracy. This result is a crucial reminder that for smaller datasets, classical methods can be more effective and computationally efficient. The power of traditional machine learning is further amplified when combined with deep domain knowledge. Kamble et al.[4] extracted a comprehensive set of kinematic features like stroke velocity, acceleration, jerk, and radial velocity from static, dynamic, and stability spiral tests recorded with a digitizing tablet. Using classifiers like logistic regression and random forest, they achieved 91.6% accuracy and an AUC of 98.1%, even introducing two new kinematic features related to radial velocity that were identified as important for early PD diagnosis, showcasing how clinical expertise can directly guide and improve model performance.



Parkinsons Healthy

Fig 2 MRI scans of healthy and Parkinson's patients (adapted from [2]).

As shown in Fig. 2, the MRI scans illustrate the structural differences between healthy and Parkinson's patients [2]. The insights gained from drawing analysis have been powerfully complemented by significant advances in neuroimaging, lead ing to a more holistic understanding of PD's structural and functional impacts on the brain. A combined approach was presented by Waykule et al. [2], who used both MRI scans and spiral test images for PD detection, creating a multimodal diagnostic pipeline. For MRIs, this included advanced image processing like skull stripping to remove non-brain tissue, brightness adjustment, and slicing, while spiral images were enhanced, resized, and converted to grayscale. They then used SqueezeNet for spirals and 3D CNNs for MRIs to achieve accuracies of 95% and 95.27%, respectively. This approach is powerful because it combines the structural evidence from MRI (e.g., changes in the substantia nigra) with the functional evidence from spiral drawings (e.g., motor impairment), pro viding a more comprehensive and robust diagnosis than either modality alone.

Within neuroimaging, novel hybrid deep learning archi tectures are being developed to capture the complex nature of brain data. Basnin et al.[13] introduced a hybrid DenseNet LSTM model to analyze the publicly available NTUA MRI dataset, which contains T1, T2, and Flair images from 78 in dividuals. After preprocessing the samples with normalization and data augmentation, the DenseNet component was used for its efficient spatial feature extraction, utilizing its unique "dense connectivity" pattern to reuse features and reduce the vanishing gradient problem. The LSTM layer was then added to capture potential temporal dependencies within the image sequence data (e.g., the sequential relationship between 2D slices in a 3D volume). This combination achieved a training accuracy of 93.75%, a testing accuracy of 90%, and a valida tion accuracy of 93.8%, outperforming other standard CNNs and highlighting the effectiveness of merging convolutional and recurrent networks for medical image analysis.Classical machine learning methods continue to play a vital role in neuroimaging, often providing more interpretable results that are crucial for clinical adoption. Beheshti and Ko [7] utilized a support vector machine (SVM) trained on 170 gray matter features extracted from T1-weighted MRI scans using voxel based and region based morphometry. Their goal was to predict cognitive decline in PD patients, and they achieved 80.76% accuracy. Crucially, they employed SHAP (SHapley Additive exPlanations) analysis, a game theoretic approach to explain the output of any machine learning model, to identify the most critical brain regions for classification, such as the left superior frontal gyrus and midbrain structures. This provides valuable biological insights alongside the predictive model, helping clinicians understand why the model is making a certain prediction and building trust in the system.

The field of neuroimaging based PD detection is further characterized by the use of highly advanced techniques and large scale, multicenter datasets that improve generalizability. Islam et al. [9] proposed a 3D CNN to classify PD from resting state fMRI data, using independent component analysis (ICA) via the MELODIC tool to break down the complex 4D fMRI data into 30 spatially independent components, from which they identified 14 relevant resting state networks. Their model, which included convolutional, max pooling, dropout, and dense layers, achieved 86.07% accuracy. In a large-scale study, Fu et al. [8] employed radiomics on T2-FLAIR MRI images from 1727 subjects, manually segmenting key brain areas like the substantia nigra and putamen, extracting 1781 high-dimensional features, and then using LASSO and mRMR techniques to select the optimal 20 to combat the "curse of dimensionality." Their SVM and MLP models achieved 90% accuracy with an AUC near 0.97 in internal testing.

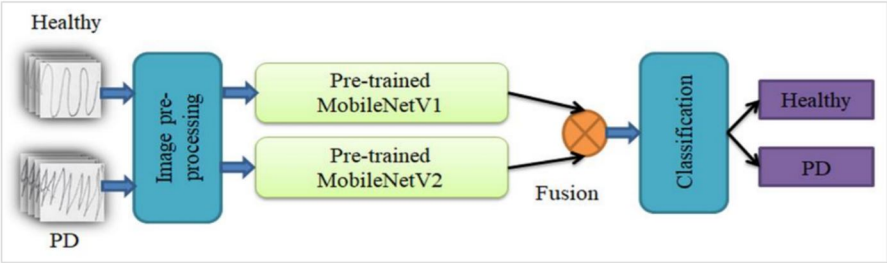


Fig. 3 Architecture for Parkinson's disease detection using dual MobileNet feature fusion (adapted from [12]).

Recognizing the need for practical, deployable solutions that can run in clinical or even mobile settings, some research has focused on efficiency. Rajinikanth et al.[12] proposed a framework using lightweight deep learning models (e.g., SqueezeNet, MobileNetV1/2, ShuffleNetV1, NASNet) which are designed with fewer parameters and specialized operations like depthwise separable convolutions to reduce computational cost. These models, pre-trained on ImageNet and adapted using a two-fold training strategy, fused their deep feature vectors and used a simple KNN classifier, which reported a perfect 100% accuracy on their dataset. This approach high lights the potential for creating highly accurate PD screening tools that are suitable for devices with limited computational resources, such as tablets in a clinic or even smartphones for remote patient monitoring.

To contextualize these diverse ad vancements, Loh et al. [10] provided a comprehensive review of 63 studies, noting the widespread success of CNNs across various modalities. However, the review also emphasized key challenges hindering clinical adoption, such as the "black box" nature of deep learning, variability in datasets due to different scanners and protocols, and limited multimodal inte gration. The authors strongly advocated for the development of explainable AI models with visual cues to increase trust and acceptance among clinicians. This push for robust and scalable models is further supported by studies like that of Anisha et al. [20], who used a VGG16-based framework with a CatBoost classifier to achieve 94.2% accuracy on a large multi stage dataset of 280 participants, including those in mild, moderate, and severe stages of Parkinson's. This demonstrates the scalability of deep learning approaches and their potential to not only diagnose but also to track disease progression, which is critical for effective long term management.

In conclusion, this integrated survey of 20 recent papers illustrates a dynamic and rapidly evolving field. The narrative reveals a clear trend away from single-modality, single-model approaches towards more sophisticated, integrated systems. The consistently high accuracies reported many exceeding 90%—demonstrate the immense potential of these tools. The key themes emerging are the power of multimodal data fu sion, the synergy between deep learning's automatic feature extraction and the interpretability of traditional methods, and the growing focus on model efficiency and explainability. Future research must continue to address the critical chal lenges of model interpretability, generalizability across diverse datasets, and seamless integration into clinical workflows to translate these promising technologies from research papers into standard practice, enabling earlier, more accurate, and more accessible diagnosis of Parkinson's Disease.

III. ANALYSIS AND DISCUSSION

TABLE 1
Comparison Between Models for PD Dectection

Model	Features and Classifier	Dataset	Accuracy
VGG19	Spiral images with CNN (transfer learning)	Kaggle spiral (PD/HC, 102)	72%
DenseNet169	Spiral images with CNN (transfer learning)	Kaggle spiral (PD/HC, 102)	85%
InceptionV3	Spiral images with CNN (transfer learning)	Kaggle spiral (PD/HC, 102)	89%
ResNet50v2	Spiral images with CNN (transfer learning)	Kaggle spiral (PD/HC, 102)	80%
CNN	Spiral + Wave images with CNN	Custom spiral, wave	93.3%
Random Forest	Spiral images (HOG feat.) with Random Forest	Kaggle spiral	87%
SVM	Spiral images (HOG feat.) with SVM (RBF)	Kaggle spiral	77%
KNN	Spiral images (HOG feat.) with KNN	Kaggle spiral	80%
CNN	Spiral + pen tagon drawing with CNN	Custom tablet dataset (87 subj.)	93.5%
ResNet50	Spiral images with CNN (TL)	Handwriting test dataset	97%
VGG16	Spiral images with CNN (TL)	Handwriting test dataset	91%
DenseNet-LSTM	MRI images with DenseNet+LSTM	NTUA MRI (PD/HC)	90%
SVM	T1 MRI brain with SVM	PPMI MRI for MCI prediction	80.8%

The table, titled "Comparison Between Models in Recent Studies for Parkinson's Disease Detection (Table I)," presents a systematic benchmark of various machine learning (ML) and deep learning models applied to the crucial task of detecting Parkinson's Disease (PD). The core objective of nearly all entries is binary classification: distinguishing between indi viduals with PD and Healthy Controls (PD/HC). The studies are categorized by the model architecture (e.g., CNN, SVM), the features utilized (e.g., Spiral images, MRI), the specific classifier employed, the dataset source and the recorded test accuracy. The comparison is essential for identifying the most effective computational strategies for objective early diagnosis.

A major segment of the table focuses on handwriting analysis, a non invasive method using drawings as motor biomarkers. This category is split between deep learning models using transfer learning (TL) on raw images (VGG19, DenseNet169, InceptionV3, ResNet50v2) and classical ML models (Random Forest, SVM, KNN) utilizing hand crafted features like HOG.

The CNN based transfer learning models show strong performance, with InceptionV3 achieving 89% accuracy on the Kaggle spiral dataset. Notably, the high est accuracies such as 93.5% are achieved by CNNs that fuse multi modal drawing inputs (e.g., spiral + pentagon), underscoring the benefit of integrating multiple aspects of motor impairment for enhanced diagnostic certainty.The most successful classifiers in the table, including ResNet50 with 97% accuracy and custom CNNs with 93.5%, highlight the superior capability of deep learning in automatically extracting complex, subtle features from drawing images that are highly correlated with PD. These performance metrics significantly outperform classical ML models (e.g., SVM at 77%) reinforc ing the trend toward deep learning for image based feature extraction. This superior performance is likely due to the neu ral networks' ability to learn robust, non linear representations of micrographia and tremor patterns.Finally, the table includes research diversifying beyond handwriting by incorporating neuroimaging data, such as T1 MRI brain scans and general MRI images. Models like DenseNet-LSTM and SVM applied to these modalities achieve competitive, yet generally lower, accuracies (e.g., 90% and 80.8% respectively). This section of the table confirms the breadth of research into PD diagnostics, while also providing a valuable contrast, suggesting that at this stage, highly specific motor task based imaging (handwriting) coupled with advanced deep learning yields the most accurate classification results for PD.

IV. CONCLUSIONS

Recent advances confirm that deep learning models such as ResNet50, DenseNet, and VGG16, especially when combined with transfer learning, achieve high diagnostic accuracy for Parkinson's disease from spiral test images, wave drawings and MRI scans often surpassing traditional machine learning techniques [3],[15]. These deep models automatically extract subtle motor or neuroimaging features vital for early diagnosis and have shown robust performance on research datasets [4]. Work on multimodal fusion demonstrates that combining spiral, wave and imaging data can provide a more holistic and sensitive screening tool for Parkinson's [12],[16].Despite this notable progress, the deployment of such models in real world clinical environments poses important challenges. Many studies relied on relatively small, homogeneous datasets often limited to a single site or demographic profile raising concerns about generalizability across populations and disease stages [9],[18]. Furthermore, model interpretability remains a barrier to clinical acceptance; neurologists and clinicians require AI tools that offer transparent decision-making processes and ac tionable insights [7]. There is a consensus that explainable AI development, along with improved data curation and standard ization of spiral and MRI protocols will help bridge the gap from research to clinical practice [14],[16].The most promising future directions involve integrating deep learning frameworks with telemedicine solutions and wearable device ecosystems. Real time analysis of digitized spiral drawings or continuous motor signals, combined with remote expert supervision, may enable continuous monitoring, early detection and proactive disease management particularly benefiting patients in remote or underserved settings [13],[17]. Longitudinal and multi cen ter studies will be essential to validate the robustness and clinical value of these AI models in diverse settings [9],[20].In summary, deep learning approaches show clear advantages for automated detection and monitoring of Parkinson's disease, yet their full clinical impact depends on solving open problems in data diversity, model transparency, and real world integration [14]

REFERENCES

[1] Mrs. S. SasiRekha, Dr. R. Shankar, and Dr. S. Duraisamy, "Parkinsons Disease Prediction With Spiral Drawings and Wave Frequency Using Deep Conformal Neural Networks," Journal of Neonatal Surgery, vol. 14, issue 4s, pp. 11–22, 2025
[2] V. V. Waykule, Siddhi Magdum, Abhishek Mule, Prachi Patil, and Mayank Ughade, "Detection of Parkinson's Disease Using MRI and Spiral Images," International Journal for Research in Applied Science and Engineering Technology, vol. 12, issue XI, November 2024, pp. 888-894.
[3] Theyazn H. H. Aldhyani, Abdullah H. Al-Nefaie, and Deepika Koundal, "Modeling and Diagnosis Parkinson Disease by Using Hand Drawing: Deep Learning Model," AIMS Mathematics, vol. 9, no. 3, pp. 6850–6877, 2024. DOI: 10.3934/math.2024334.
[4] Megha Kamble, Prashant Shrivastava, and Megha Jain, "Digi tized Spiral Drawing Classification for Parkinson's Disease Diag nosis," Measurement: Sensors, vol. 16, pp. 100047, 2021. DOI: 10.1016/j.measen.2021.100047.
[5] Priyal Agarwal, Vipin Talreja, Rutuja Patil, Vaishnavi Jadhav, and Indu Dokare, "Early Detection of Parkinson's Disease Using Spiral Test," in Data Science and Big Data Analytics, Springer, pp. 391–402, 2024. DOI: 10.1007/978-981-99-9179-2-30.
[6] Nesren Farhah, "Utilizing Deep Learning Models in an Intelligent Spiral Drawing Classification System for Parkinson's Disease Clas sification," Frontiers in Medicine, vol. 11, pp. 1453743, 2024. DOI: 10.3389/fmed.2024.1453743.
[7] Iman Beheshti and Ji Hyun Ko, "Predicting the Occurrence of Mild Cognitive Impairment in Parkinson's Disease Using Structural MRI Data," Frontiers in Neuroscience, vol. 18, pp. 1375395, 2024. DOI: 10.3389/fnins.2024.1375395.
[8] Junyan Fu, Hongyi Chen, Chengling Xu, Zhongzheng Jia, Qingqing Lu, Haiyan Zhang, Yue Hu, Kun Lv, Jun Zhang, and Daoying Geng, "Harnessing Routine MRI for the Early Screening of Parkinson's Disease: A Multicenter Machine Learning Study Using T2-Weighted FLAIR Imaging," Insights into Imaging, vol. 16, no. 92, 2025. DOI: 10.1186/s13244-025-01961-3.

[9] Nair Ul Islam, Ruqaiya Khanam, and Ashok Kumar, "Using 3D CNN for Classification of Parkinson's Disease from Resting-State fMRI Data," Journal of Engineering and Applied Science, vol. 70, no. 89, 2023. DOI: 10.1186/s44147-023-00236-2.

[10] Hui Wen Loh, Wanrong Hong, Chui Ping Ooi, Subrata Chakraborty, Prabal Datta Barua, Ravinesh C. Deo, Jeffrey Soar, Elizabeth E. Palmer, and U. Rajendra Acharya, "Application of Deep Learning Models for Automated Identification of Parkinson's Disease: A Review (2011–2021)," Sensors, vol. 21, no. 21, pp. 7034, 2021. DOI: 10.3390/s21217034.

[11] Yingcong Huang, Kunal Chaturvedi, Al-Akhir Nayan, Mohammad Hesam Hesamian, Ali Braytee, and Mukesh Prasad, "Early Parkin son's Disease Diagnosis through Hand-Drawn Spiral and Wave Anal ysis Using Deep Learning Techniques," Information, vol. 15, no. 4, 220, 2024. DOI: 10.3390/info15040220.

[12] Venkatesan Rajinikanth, Sahar Yassine, and Syed Ahmad Chan Bukhari, "Hand-Sketches based Parkinson's disease Screening using Lightweight Deep-Learning with Two-Fold Training and Fused Opti mal Features," International Journal of Mathematics, Statistics, and Computer Science, vol. 2, 2024. DOI: 10.59543/ijmscs.v2i.7821.

[13] Nanziba Basnin, Nazmun Nahar, Fahmida Ahmed Anika, Mohammad Shahadat Hossain, and Karl Andersson, "Deep Learning Approach to Classify Parkinson's Disease from MRI Samples," Lecture Notes in Computer Science, pp. 536–547, 2021. DOI: 10.1007/978-3-030 86993-9-48.

[14] Ramya R., Ramesh C., Murugesan P., Nithya N., and Sathish Kumar G., "Enhancing Parkinson's Disease Prediction Using Deep Learning Based Convolutional Neural Networks," J. Electrical Systems, vol. 20-5s, pp. 1866-1874, 2024.

[15] Omar Alniemi and Hanaa F. Mahmood, "Convolutional neural net work for the detection of Parkinson disease based on hand-drawn spiral images," Indonesian Journal of Electrical Engineering and Computer Science, vol. 30, no. 1, pp. 267-275, April 2023. DOI: 10.11591/ijeecs.v30.i1.pp267-275.

[16] Manuel Gil-Mart´ ın, Juan Manuel Montero, and Rub´en San-Segundo, "Parkinson's Disease Detection from Drawing Movements Using Convolutional Neural Networks," Electronics, vol. 8, no. 8, 907, 2019. DOI: 10.3390/electronics8080907.

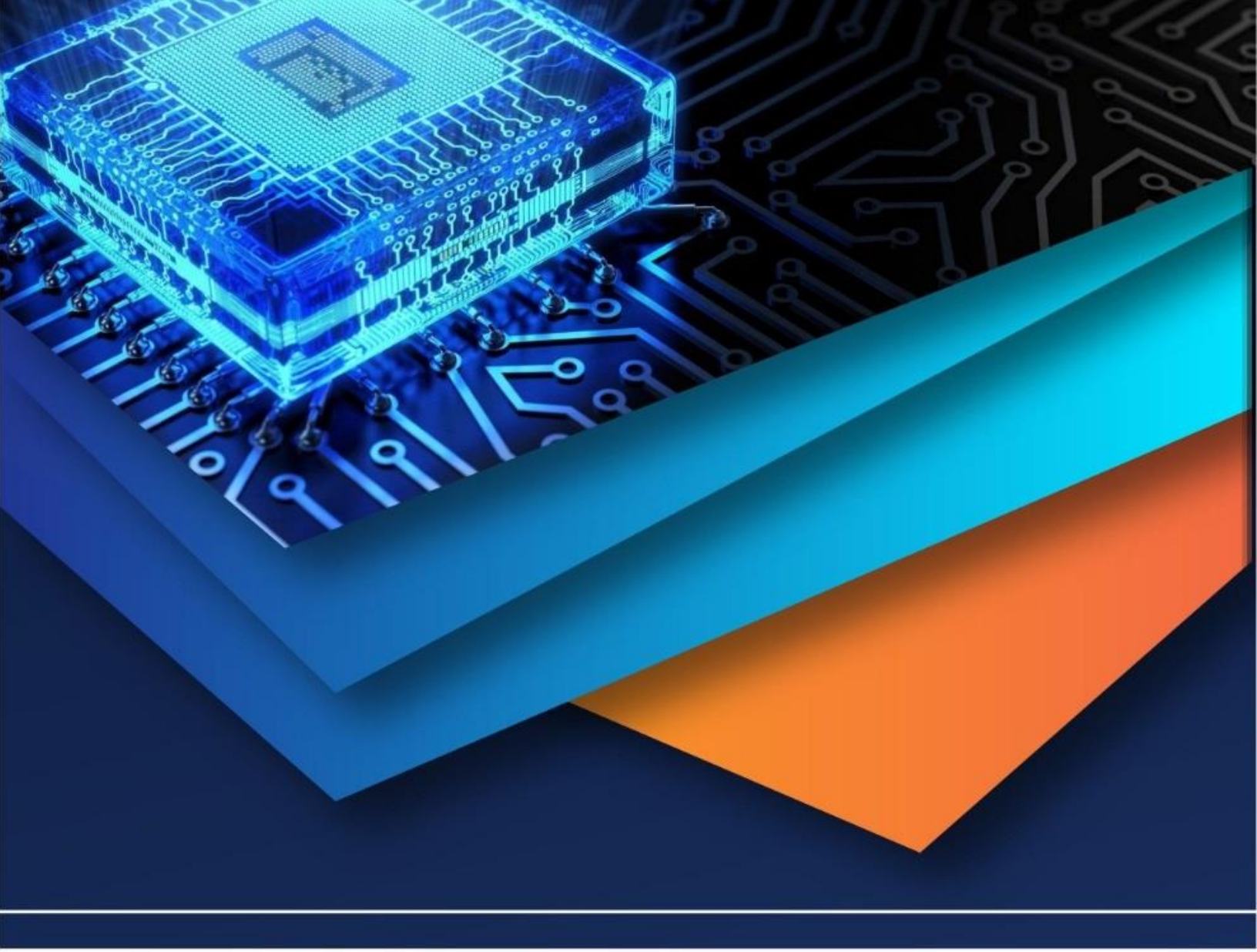
[17] Sabyasachi Chakraborty, Satyabrata Aich, Jong-Seong-Sim, Eun young Han, Jinse Park, and Hee-Cheol Kim, "Parkinson's Disease Detection from Spiral and Wave Drawings using Convolutional Neural Networks: A Multistage Classifier Approach," in Proceedings of the 22nd International Conference on Advanced Communications Technology (ICACT), pp. 298–303, 2020. DOI: 10.23919/ICACT48636.2020.9061497.

[18] Mohamad Alissa, Michael A. Lones, Jeremy Cosgrove, Jane E. Alty, Stuart Jamieson, Stephen L. Smith, and Marta Vallejo, "Parkinson's disease diagnosis using convolutional neural networks and figure copying tasks," Neural Computing and Applications, vol. 34, pp. 1433–1453, 2022. DOI: 10.1007/s00521-021-06469-7.

[19] Meenakshi Malik, Edeh Michael Onyema, Mueen Uddin, Poonam Yadav, Aanchal Sharma, Jazlyn Jose, Achyut Shankar, Fahad Alasim, and Mustufa Haider Abidi, "Deep learning approach for Parkinson's screening with geometric features from spiral and wave drawings," Multimedia Tools and Applications, advance online publication, 2025. DOI: 10.1007/s11042-025-20915-x.

[20] A. Anisha, Femima Shelly A. T, Benitta R. K, and Amala Selciya T. L., "Parkinson's Disease Detection using Spiral Drawings," InternatiIonal Journal of Innovative Science and Research Technology, vol. 8, issue 5, May–2023: 2658-2663, 2023

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