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RESEARCH ARTICLE

A Self-Operational Convolutional Neural Networks With Convergent Cross-Mapping and Its Application in Parkinson's Disease Classification

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ABSTRACT Parkinson's disease (PD) is a progressive neurodegenerative disease with multiple motor and non-motor characteristics. PD patients commonly face vocal impairments during the early stages of the disease. Therefore, diagnosis systems based on vocal disorders are at the forefront of recent PD detection studies. Our study proposes two frameworks based on Convolutional Neural Networks to classify Parkinson's disease (PD). In recent years, Convolutional Neural Networks (CNNs) have proven highly effective in various medical applications, particularly disease classification. However, standard CNN designs have significant limitations because they require extensive manual calibration and supervision, which can result in biases and poor performance in practical applications. This paper proposes the Self-Operating Convolutional Neural Network (SOCNN) in conjunction with Convergent Cross-Mapping (CCM) to address these issues. The SOCNN architecture is intended to modify its internal parameters automatically, eliminating the need for manual intervention during training and increasing the model's adaptability to unknown data. Adopting CCM principles, we construct a seamless connection between the input and output domains, allowing for rapid information transfer and preservation, which are crucial for accurate disease classification. To this end, we construct causal networks, extract network features, and perform deep learning analysis to distinguish Parkinson's disease patients (PD) from age and gender-matched healthy controls (HC). Using a large dataset of Parkinson's Disease (PD) patients and healthy controls, the effectiveness of the proposed SOCNN with CCM is evaluated. Specifically, we use the SOCNN-CCM to compute the centrality of the network nodes, which act as features for the classification models. Extensive experiments are conducted to compare the SOCNN to conventional CNN models and innovative techniques. The results demonstrate that the SOCNN-CMM outperforms state-of-the-art in terms of accuracy, sensitivity, and specificity when classifying Parkinson's patients, confirming its diagnostic potential.

INDEX TERMS Parkinson's disease, self-operating convolutional neural network, convergent cross-mapping, health controls.

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I. INTRODUCTION

The death of neurons in the substantia nigra, the region responsible for dopamine production, characterizes

Parkinson's disease (PD) [1]. A key molecule called dopamine, a member of the phenethylamine and catecholamine families, operates as a messenger between the brain and the substantia nigra and is a key regulator of motor activities [2]. Approximately 60-80% of the cells that generate dopamine are destroyed before Parkinson's disease symptoms appear [3]. This occurs when there is not enough dopamine to control a person's movements. The ability to control the body's motor processes is hampered by a decrease in the production of dopamine neurons [4]. Four distinct motor symptoms, including tremors, which appear as quivering of the jaw, hands, legs, and arms, and stiffness leading to rigidity in the limbs and torso, are the hallmarks of Parkinson's disease [5]. Non-motor signs like dementia, depressive thoughts, restless legs, increased sensitivity to heat, and digestive problems might accompany these motor symptoms [6]. Even though Parkinson's disease is currently incurable, a few therapeutic options are available for patients experiencing motor and non-motor symptoms. There are non-invasive (drugs) and invasive (surgery) techniques for detection and treatment. By blocking nerve signals, medications influence the motor system [7]. Side effects are possible with all prescription medicines and surgical treatments. Assessments of voice disorders became a useful and unobtrusive method for early Parkinson's disease diagnosis. This is explained by the finding that 90% of people with PD experience dysphonia or vocal impairment, which sets them apart from people in a healthy state [8]. In order to diagnose Parkinson's disease, voice tests have emerged as a reliable and useful tool. Parkinson's disease (PD) affects about 10 million people worldwide and is the second most common neurological condition [9]. Men are more prone than women to get Parkinson's disease, and people over 65 are the main demographic affected by the condition. Years before motor symptoms appear, early symptoms like loss of smell, constipation, and sleep difficulties are noticeable. Later, other symptoms like tremors, a loss of coordination, and speech problems start to show themselves. It is critical to receive the correct treatments early on to help reduce or stop the disease's progression. However, symptom-based diagnosis of PD is still a complicated and involved process [10]. Speech problems affect 90% of Parkinson's patients. Hence analyzing voice data has lately emerged as a critical tool for diagnosing the condition [11]. Early identification of Parkinson's disease (PD) can be aided by the analysis of acoustic signals [12]. While listeners may not hear vocal issues in the early stages of Parkinson's disease, voice markers can be used to identify these challenges [13]. Neurodegeneration without discernible clinical indicators characterizes preclinical circumstances, which are the first stage. After that, Parkinson's disease and movement disorders enter the prodromal phase, during which individuals start to show clinical symptoms, but the available diagnostic information is still insufficient [14]. Because of this, early detection in all stages is essential for doctors to identify the illness and deliver prompt medical care. At this time, PD cannot be early diagnosed with the use of trustworthy biomarkers. One example of PD is shown in Figure 1. This paper suggests a new technique for classifying Parkinson's illness that combines Convergent Cross-Mapping (CCM) and Self-Operational Convolutional Neural Networks (SOCNN), two cutting-edge techniques. Specifically designed to improve its architecture and dynamically learn from the dataset, SOCNN stands out as a unique adaption of the traditional convolutional neural network. It gradually evolves to achieve better feature extraction and representation. Convolutional neural networks [36] are practical tools for image classification. However, they frequently need more adaptability because they involve human tuning of hyperparameters and rigid designs. SOCNN overcomes these problems by incorporating an autonomous learning mechanism that dynamically adjusts its settings, improving its PD classification performance. This study also uses the Convergent Cross-Mapping (CCM) technique, a strong nonlinear time-series analytic tool used in domains as diverse as climate science and economics. CCM enables the identification of complicated causal relationships among various neurophysiological signals and biomarkers linked to Parkinson's disease. This study combines SOCNN with CCM to create a more inclusive and intelligible model for Parkinson's disease classification. We tested the unique SOCNN and CCM framework on a large dataset that included both healthy individuals and those diagnosed with Parkinson's disease. This dataset incorporates a wide range of clinical and neuroimaging measures. Through meticulous comparison with other cutting-edge approaches and diligent experimentation, we painstakingly evaluated the effectiveness and resiliency of this unique methodology. This study holds enormous potential, with the capacity to enhance patient prognoses and facilitate early intervention through greater precision and effectiveness in diagnosing Parkinson's disease. Furthermore, the combination of SOCNN and CCM demonstrates great promise for developing durable and flexible machine-learning models in the medical field. This lays the groundwork for future studies and breakthroughs in the fields of sickness classification and individualized treatment.

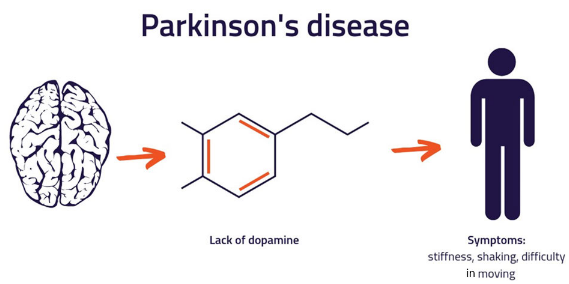

FIGURE 1. Sample Image of PD.

A. MOTIVATION

- A neurological disorder recognized as Parkinson's disease affects millions of individuals worldwide. Effective management and intervention depend on timely and precise diagnosis. Innovative technological alternatives must be explored because traditional diagnostic procedures may not have the sensitivity and specificity needed for early identification.

- The concept of a self-operating CNN adds flexibility and autonomy to the network's operation. The impartiality of this innovation is to construct a neural network that can adjust to the particular features of Parkinson's disease data and learn from it throughout the training process, possibly leading to a development in performance over time.
- The addition of convergent cross-mapping improves the network's ability to capture complicated links in data. This approach is intended to rise the model's interpretability and generalization, making it more resilient and relevant to varied datasets. This is critical when dealing with the inherent heterogeneity in medical data.
- The impartial of this study is to increase a trustworthy system for classifying Parkinson's disease. The aim is to use medical imaging data to reliably differentiate among people that are doing well and those who have been diagnosed with Parkinson's disease. The intention is to improve the analysis's sensitivity, specificity, and accuracy by utilizing self-operational Convolutional Neural Networks (CNNs) [37], [38] with convergent cross-mapping.

B. MAJOR CONTRIBUTIONS

The main contributions of this paper are as follows:

- The Self-Operating Convolutional Neural Network (SOCNN), in conjunction with Convergent Cross-Mapping (CCM), are developed to find solutions to this issue.
- The SOCNN architecture is designed to automatically alter its internal parameters, minimizing the need for manual intervention during training and enhancing the model's adaptability to unfamiliar data.
- Adopting CCM principles to build a seamless connection between the input and output domains allows for speedy information transfer and preservation, critical for accurate disease categorization.
- To distinguish between people with Parkinson's disease (PD) and healthy controls (HC) who are matched for age and gender, causal networks are created, network features are extracted, and deep learning analysis are used.
- A large dataset comprising both healthy individuals and patients with Parkinson's disease is used to evaluate the suggested SOCNN-CCM. The centrality-based network node is computed by the SOCNN-CCM, which is utilized as a feature in classification models.
- Finally, statistics demonstrate that when identifying Parkinson's patients, the SOCNN-CMM outperforms in accuracy, sensitivity, and specificity, demonstrating its diagnostic potential.

The remainder of this paper is divided into the following sections: A thorough analysis of the relevant literature is provided in Section II. The strategy, including the self-operating CNN architecture with CCM and the pre-processing techniques used, is covered in Section III. Section IV describes the experimental setup, outcomes, and performance measures. Section V concludes with a comprehensive conclusion and future research directions.

II. LITERATURE SURVEY

To diagnose Parkinson's disease (PD), Gunduz [15] propose two frameworks that utilize vocal (voice) data and convolutional neural networks. These frameworks share the common objective of amalgamating multiple feature sets but adopt distinct approaches. In the latter method, parallel input layers connected directly to convolutional layers receive the feature sets. In contrast, the earlier structure combines various feature sets before inputting them into a nine-layered CNN. Consequently, deep features from each parallel branch are concurrently gathered before integration into the merge layer. The proposed models undergo training using data from the UCI Machine Learning collection, and their effectiveness is evaluated through the Leave-One-Person-Out Cross Validation (LOPO CV) technique. Alalayah et al. [16] present novel ways to improve early detection tactics for Parkinson's disease in their study. They accomplish this by focusing on specific elements, refining hyperparameters of machine learning algorithms, and overcoming speech-related diagnostic challenges. To analyze the relevance of features in connection with the desired trait, the researchers used the recursive feature elimination (RFE) method. In addition, to ensure a balanced dataset, they used the synthetic minority oversampling technique (SMOTE). Several classifiers, such as support-vector machines (SVM), K-nearest neighbors (KNN), decision trees (DT), random forests (RF), and multilayer perceptrons (MLP), were used to classify the features produced by t-SNE and PCA.

Mei et al. [17] investigated the usefulness of machine learning (ML) in diagnosing Parkinson's disease, as modest non-motor symptoms may go unnoticed in a physician's subjective evaluation. The study examined 209 papers, employing datasets, various machine learning approaches, and deriving useful findings. Using three machine learning (ML) techniques, Khachnaoui et al. [18] examined a Parkinson's disease dataset with the goal of differentiating between those with the disease and those that are healthy. For a thorough analysis, the dataset was put through Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Models such as DBSCAN and K-means rely on feature-reduction techniques. Compared to PCA, LDA excels. Therefore, clustering algorithms use its result as input. A 64% accuracy, 78.13% sensitivity, and 38.89% specificity were achieved with DBSCAN. Pramanik et al. [19] developed three techniques for utilizing ForestPA characteristics to detect Parkinson's disease based on decision-forest and SysFor algorithms. With this method, only a limited number of decision trees are needed to achieve high accuracy. Assessing recent, real-time data and dynamically increasing the number of decision trees during training is the most efficient method for Parkinson's disease diagnosis. By leveraging ForestPA's features, the precision of the decision tree reached 94.12%.

For classification, Khoshnevis and Sankar [20] utilized EEG recordings from a population of 20 people with Parkinson's disease (PD) and 20 age-matched healthy controls. Six lower-order and thirty higher-order statistical factors were employed. EEG recordings were utilized to gather data from the participants and patients. We found that the RUS Boosted trees ensemble, notably for the late PD class, achieved the maximum sensitivity for this task due to the imbalanced structure of our dataset. The RUS Boosted trees ensemble performed the best, even though alternative techniques may have an overall greater accuracy. The accuracy of categorization significantly increased due to the use of the recently discovered attributes. Machine learning techniques are critical to the telemedicine sector, as demonstrated by Govindu and Palwe [21] method for early Parkinson's disease diagnosis. Using MDVP audio data collected from thirty Parkinson's disease (PWP) patients and an equivalent number of healthy participants, we trained four machine learning (ML) models. The Random Forest classifier was shown to be the most successful method for detecting Parkinson's disease after a comparison of the classification results of Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression models. With a sensitivity of 0.95 and a detection accuracy of 91.83%, the Random Forest classifier model performed well. These results point to a promising direction for the further application of machine learning in telemedicine, which could have a major positive impact on Parkinson's patients. In their research, Petrucci et al. [22] examined how frequently individuals with Parkinson's disease experience gait freezing. They focused on forecasting and controlling this phenomenon, with ground reaction force (GRF) as the primary evaluation criterion. Additionally, they observed the effects of ankle orthotics on the condition. Patients wearing ankle orthotics exhibited significantly lower average vibration amplitudes after the addition of supplemental ground reaction force (GRF). This implies that the severity of Parkinson's disease (PD) in individuals is closely linked to the accompanying ground reaction force.

Furthermore, Oh et al. [23] utilized depth sensor-driven musculoskeletal modeling to compare the GRF between individuals with Parkinson's disease and healthy individuals. The earliest peaks of the Ground Reaction Force (GRF) displayed significant differences. Numerous studies have demonstrated that the abnormal walking patterns observed in people with Parkinson's disease are reflected in their GRF during walking, underscoring the significance of GRF as a fundamental element in Parkinson's disease research. Using a voice dataset with 22 unique factors, Alalayah et al. [16] aim to provide insight into the early diagnosis of Parkinson's disease. They are not appropriate for advanced diagnosis; nonetheless, due to these closely related traits, outliers in features were removed. For component ranking, we used the importance-driven Recursive Feature Elimination (RFE) method. Data were then projected into a lower-dimensional space, and dimensionality reduction was accomplished using t-SNE and PCA algorithms. The acquired condensed features were then used to train classifiers, such as Random Forest (RF), Decision Tree (DT), k-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). These classifiers' ability to discriminate between participants who were healthy and those who had Parkinson's disease varied. Notably, t-SNE and RF together produced remarkable results with 97%, 96.50%, 94%, and 95% for accuracy, precision, recall, and F1-score, respectively. On the other hand, MLP performed admirably when combined with PCA, obtaining 98%, 96.66%, 96%, and 98% for accuracy, precision, recall, and F1-score, respectively. This study shows acoustic waves can reliably and quickly identify Parkinson's disease.

The study conducted by Borzì et al. [24] involved the extraction, careful selection, and optimization of machine-learning classifiers for the detection of Freezing of Gait (FOG) using frequency features of velocity and angle inputs. The patients were evaluated, and positive outcomes were shown by the FOG detection network. The network demonstrated impressive results: 86.1% overall accuracy, 85.9% specificity, and 84.1% sensitivity. As a result, the network can forecast when FOG will occur. A method for determining if someone has Parkinson's disease was developed by Aljalal et al. [25] based on spatial patterns for both those taking medication and those not. The noise in the EEG measurements was minimized using a consistent spatial pattern. Machine-learning classifiers were fed the properties of the enhanced signals. The classifier's precision level was increased to 95% by combining traits in the beta and alpha ranges to produce the best results. In their study to evaluate neurological impairment in Parkinson's disease patients, Barbero-Gómez et al. [26] introduced a 3D CNN ordinal model. The researchers have created a method for geographical data augmentation to satisfy the requirement for large datasets and improve CNN performance [29]. They investigate the OGO-SP approach, which generates interclass data using a gamma probability distribution, facilitating ordinal graph-based oversampling via shortest paths. The researchers suggest using the beta distribution, a novel method dubbed OGO-SP-, to create synthetic samples in the inter-class zone. This distribution is considered more suitable for this purpose than gamma. An innovative 3D picture dataset obtained from the Hospital Universitario "Reina Sofia" in Cordoba, Spain, is used to assess the efficacy of the various techniques. Pramanik et al. [19] developed three methods for Parkinson's disease diagnosis using ForestPA characteristics, decision-forest, and SysFor algorithms. To attain good accuracy, this strategy merely employs a minimal number of decision trees. Enhancing decision tree density through dynamic training and additional sample evaluation is the most efficient method for Parkinson's disease (PD) identification. Decision tree classification accuracy increased significantly to 94.12% when ForestPA features were used. Three machine learning (ML) and artificial neural network (ANN) techniques were used to diagnose a voice dataset in a study by Arti et al. [27]. Wrapping and filtering techniques were used to enable better feature selection and enhanced data collecting. While the naive Bayes method showed a lesser accuracy of 74.11%, the SVM paired with KNN produced an accuracy of 87.17%.

A. LIMITATIONS OF EXISTING SYSTEMS

- One potential restriction could be the restricted dataset available for training and assessing the suggested neural network. Although valuable, Parkinson's disease datasets may be minimal in size, impairing the generated model's generalizability and robustness.
- Parkinson's disease symptoms and course are known to vary significantly between sufferers. The paper may need to discuss how the proposed neural network deals with variability in data distribution and whether it is sensitive to changes in data distribution.
- The selection of hyperparameters can considerably impact the performance of convolutional neural networks (CNNs). The study could look into how hyperparameter sensitivity influences the reproducibility and consistency of results.
- Although CNNs are excellent at extracting information independently, understanding the acquired features within the context of Parkinson's disease diagnosis may provide difficulties. A method or strategy to improve the interpretability of network decisions could be explored in the study.
- Evaluating the model's generalizability to other datasets or patient populations is critical. If the study lacks validation on external datasets, the proposed method's application to various circumstances may be constrained.

B. PROBLEM IDENTIFICATION OF EXISTING SYSTEM

- Diagnosis of Parkinson's disease entails studying complicated and subtle patterns in medical pictures such as brain scans or pathological images. Traditional CNN models may struggle to capture these nuanced aspects accurately.
- Due to data gathering problems, privacy issues, and the rarity of specific disorders, medical datasets, particularly those connected to Parkinson's disease, are sometimes limited in size. The lack of data can impede CNNs' training and generalization capabilities.
- Models that provide accurate forecasts and insights into the elements that contribute to those predictions are required by medical practitioners and researchers. Because CNNs are black-box models, they may lack transparency in revealing the underlying reasons that influence their judgments.
- Deploying and maintaining CNN models for real-world medical applications, such as Parkinson's disease detection, necessitates automation and adaptability to handle fresh data and continuously update the model.
- Effective Parkinson's disease classification may require mapping information from several sources or domains, such as clinical, imaging, and genetic information. Integrating these disparate data sources into a uniform diagnostic paradigm is challenging.

III. PROPOSED SYSTEM

This section discusses the Self-Operating Convolutional Neural Network (SOCNN) in conjunction with Convergent Cross-Mapping (CCM). The SOCNN architecture is designed to automatically alter its internal parameters, removing the requirement for user intervention during training and enhancing the model's flexibility to unfamiliar data. Using CCM principles, we build a seamless connection between the input and output domains, allowing for speedy information transfer and preservation, which is critical for accurate illness categorization. The SOCNN-CCM method's block diagram is shown in Figure 2.

A. DATASET

Max Little of Oxford University provided the dataset utilized in this study to help with PD early identification [28]. The UCI Machine Learning Repository later gained access to this collection of voice sound-focused data. The dataset is regarded by many medical professionals as one of the best they have collected, processed, and evaluated. Numerous scientists have created automated methods and tested them on this dataset. There are still many researchers and people coming here concerned with detecting Parkinson's disease early. This study gathered image MRI data records from the PPMI database (www.ppmi-info.org/data), renowned internationally as a pivotal multicenter initiative investigating biomarkers driving Parkinson's Disease progression. Specifically, MRI scans were chosen for this study according to specific imaging protocols. The speech signal collection consists of 195 biomedical voices divided into 48 phonetic patterns for healthy people and 147 phonetic patterns for Parkinson's disease patients.

IV. PREPROCESSING

"Data Preprocessing" is the general term for the conversion of unprocessed data into a format that can be interpreted and utilized. A complete execution of data analysis is a necessary prerequisite for the effective progression of succeeding stages. There are two steps in the processing of data:

1) The process of replacing missing data points, removing outliers, and duplicating entries is known as data imputation.
2) Data validation is a process that makes sure that information is accurate, coherent, and reliable [30].

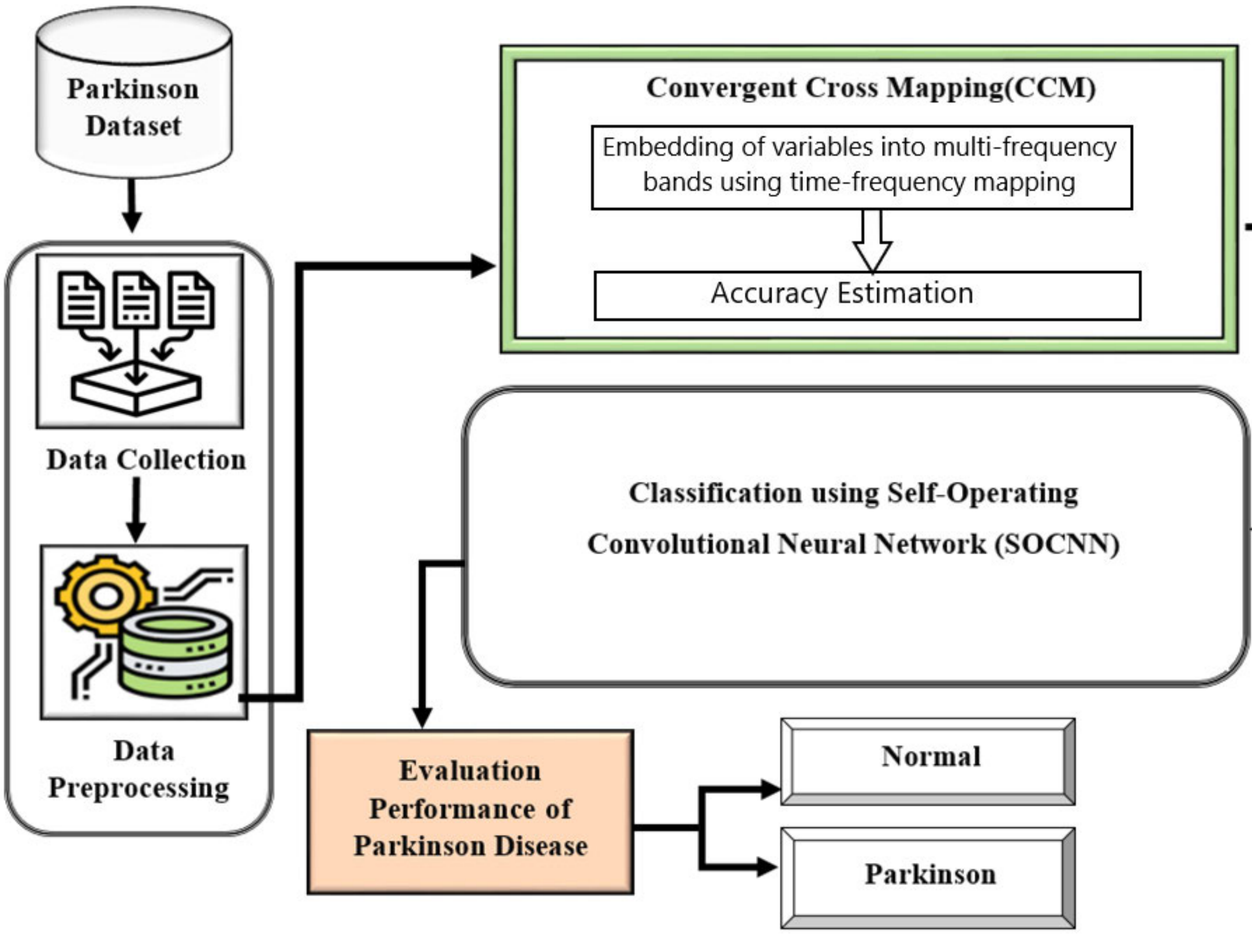

FIGURE 2. Proposed method of SOCNN-CCM.

The dataset does not contain any duplicated items, as stated in the paper, and this is supported by almost equal numbers of rows and unique column values. The "status" attribute is the only one categorized as a binary category characteristic; all other qualities are regarded as continuous "numerical variables." As a result, it is necessary to convert the data associated with this particular attribute into an object data type format. If abnormalities are detected during data processing, relevant steps are taken based on a careful investigation of the precise nature and extent of the anomalies. Duplicate data should be removed, missing data should be filled in, outliers should be handled, data validation issues should be investigated and addressed, or outliers should be handled and removed. The purpose is to guarantee the honesty and quality of the data so that we may conduct an accurate and trustworthy analysis. In the proposed work the Preprocessing of data records have been analysed using CCM techniques given in detail in the following subsection.

Convergent Cross-Mapping (CCM): The foundational state space, also known as the "attractor space," is where variables that causally affect one another, like recordings from two electrodes, move when they are part of dynamical systems. To be clear, every moment in time is a specific location within this space. Mathematical principles make it possible to infer the behavior of the complete system from the sequential progression of a single variable. As a result, the behavior of one variable limits the behavior of other variables, allowing us to use this restriction to restore the initial configuration of the attractor's overall structure. Consider the time series A and B, a pair within the M-represented deterministic dynamical system. Using the equation (1).

$$a(t) = a(t), a(t-1), \ldots.., a(t-(D-1)) \qquad (1)$$

The time-varying patterns of A can be represented as an ensemble of state vectors with D dimensions known as a delay-coordinate state space. For ease of use, we assume that there are no time delays. Its attractor manifold is the name given to this modified state-space of A Time-delay embedding refers to the process of transforming a sequence into its delay-coordinate space. In dynamical systems, the Takens theorem establishes the following universal rule: the states of the global attractor C have a one-to-one mapping to the conditions of the local attractors and as a result, the local attractors, also known as shadow manifolds, correspond to one another exactly.

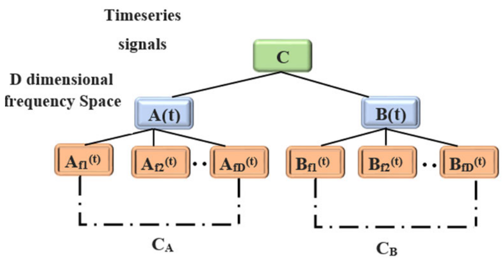

FIGURE 3. Embedding of A and B into D frequency bands using time-frequency mapping.

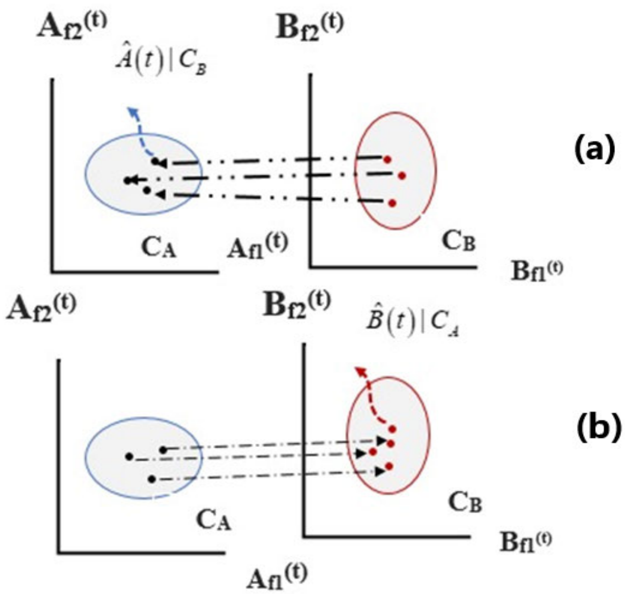

FIGURE 4. (a) Accurately estimating A (t) from CB and (b) Estimating B (t) from CA with low acuracy.

Consider two variables, A and B, with asymmetric interactions to understand the underlying idea of this technique, convergent cross mapping (CCM). That is, A affects B but not the other way around. The goal is to infer the causal relationships between observational time series A and B. Since A and B are causally related, information about A can be found in B's past. As a result, the closest neighbors in the shadow manifold can be used to reproduce the 'cause-variable' A exactly, but only if there is a causal connection between A and B. As A's causal influence on B's dynamics grows, more information about A is stored inside the manifold, which is derived from a given number of B observations. This argument underpins the CCM (Convergent Cross Mapping) approach to causal inference.

A. CLASSIFICATION USING SELF-OPERATING CONVOLUTIONAL NEURAL NETWORK (SOCNN)

A Self-Organizing Convolutional Neural Network (Self-OCNN) consists of generative neurons that may approximate various nodal functions, including linear, exponential, Gaussian, harmonic, and more. The Self-OCNN can increase

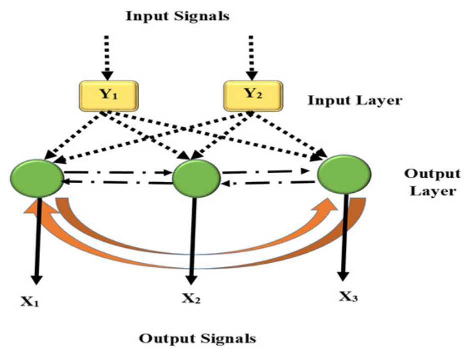

FIGURE 5. Architecture of Self-Operating Convolutional Neural Network (SOCNN).

operational diversity and adaptability to this amazing generative power. It accomplishes this to optimize the learning process by enabling the development of customized nodal operator functions for certain kernel elements. Because it is not constrained by specified operator sets or previous search operations to find the best nodal operator, Self-OCNN offers a significant advantage over conventional OCNN. The Self-OCNN architecture can be seen in Figure 4 for illustration purposes. The MacLaurin polynomial, often known as the Zth order truncated approximation, has the following finite sum form:

$$\zeta(y)^{(Z)} = \sum_{n=0}^{Z} \frac{\zeta^{n}(0)}{n!} y^{n} \tag{2}$$

The approach mentioned above can sufficiently approximate any function $\zeta(y)$ near zero. The network may learn the power coefficients, denoted as $\frac{\zeta^{n}(0)}{n!}$ and use them to create a composite nodal operator during training. This occurs when the neuron's input characteristic, such as tanh, is constrained by the activation function and maps within the region of 0. The nodal operator of the k^{th} generative neuron in the l^{th} layer was demonstrated in [31] to have the following generic form.

$$\tilde{\zeta}_{k}^{l}(a_{lk}^{l(Z)}(r), x_{i}^{l-1}(m+r)) = \sum_{z=1}^{Z}(a_{lk}^{l(Z)}(r, Z)(x_{i}^{l-1}(a+r))^{Z} \tag{3}$$

$$\tilde{y}_{ik}^{l}(m) = \sum_{r=0}^{K-1}\sum_{z=1}^{Z}(a_{lk}^{l(Z)}(r, Z)(x_{i}^{l-1}(a+r))^{Z} \tag{4}$$

where K is the layer, i^{th} neuron's kernel size. (4) can be distilled as follows:

$$\tilde{y}_{ik}^{l} = \sum_{z=1}^{Z} Conv(a_{lk}^{l(Z)}, (x_{i}^{l-1})^{Z}) \tag{5}$$

Convolution operations can thus be used to complete the equation. Finally, the following phrase explains the output of

TABLE 1. Description of mathematical symbols.

Symbol	Description
A and B	Time Series
M	Deterministic Dynamical System
A	state vectors
D	dimensions
b_k^l	neuron's bias
l^{th}	layer
i^{th}	neuron's kernel size
i^{th}	generative neurone
$\frac{\zeta^n(0)}{n!}$	power coefficients
C_A and C_B	shadow manifolds
Z	MacLaurin polynomial
$\zeta(y)$	function

TABLE 2. Experiments Coded using Python.

Resource	Details
Graphics Processing Unit (GPU)	4 GB
Implementation Language	Python
Memory (RAM)	8 GB
Processor	6th Generation Intel® Core™ i5

this neuron:

$$y_{ik}^l = b_k^l + \sum_{i=0}^{N_{l-1}} y_{ik}^{\tilde{l}} \tag{6}$$

where b_k^l is the neuron's bias. The neuron's learnable bias value can compensate for the DC bias' additive influence on the 0th-order component, z=0. A generative neuron changes into a convolutional neuron when Z equals 1. Formulas for training through backpropagation (BP) in its raw vector presentation and formulas for training via forward propagation (FP) in its raw vector format.

V. RESULT AND DISCUSSION

A. EXPERIMENTAL SETUP

This section presents the system development's findings. For the experiment, which was run on a Windows PC, the equipment specified in Table 2 was used. Python was used to code the experiments.

B. COMPARATIVE METHODS

The suggested SOCNN-CMM is contrasted with several established techniques, including the Tunable Q-factor Wavelet Transform (TQWT) [32], Least Absolute Shrinkage and Selection Operator (LASSO) [33], Support Vector Machine (SVM) [34], Multi-Layer Perceptron (MLP) [35], Synthetic Minority Over-Sampling Technique (SMOTE) [36]. TQWT [32] was applied to vocal signals of the individuals for the diagnosis of PD. The success of the extracted TQWT features was compared with commonly used vocal features in PD studies.The voice features were recovered from phonation tasks and filtered down to the six most relevant characteristics for each phonation task using the Least Absolute Shrinkage and Selection Operator (LASSO) feature ranking approach. To separate Parkinson's disease patients from healthy individuals, a Support Vector Machine (SVM) was utilized. The provided feature set is input into a specially designed, finely tuned classifier that employs a multilayer perceptron (MLP) and re-samples it using k-fold cross-validation. By improving the identification of the minority class, the Synthetic Minority Oversampling Technique (SMOTE) addresses the problem of class imbalance in PD stage-wise classification.

C. PERFORMANCE METRICS

Performance measures play an essential part in assessing classifier prediction abilities. Although accuracy is a commonly used metric, it might need to be more accurate when dealing with unbalanced class distribution data. When the class imbalance is present, metrics like Precision, Recall, F-score, Specificity (SP), Accuracy, Matthews Correlation Coefficient (MCC), and execution time provide a more thorough assessment of a classifier's capacity to distinguish between multiple classes.

In the confusion matrix, the letters TP, FP, FN, and TN denote the corresponding counts of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). These counts allow for calculation of the following performance metrics:

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

$$Sensitivity(SE) = \frac{TP}{TP + FN} \tag{9}$$

$$Specificity(SP) = \frac{TN}{TN + FP} \tag{10}$$

$$MCC = \frac{(TP * TN - FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{11}$$

The Matthews Correlation Coefficient is another statistic that may be used to assess how accurate binary classifications are. MCC is well known as a balanced measure that may be employed even when the class distribution is imbalanced since it considers the TP, FP, FN, and TN counts.

1) SPECIFICITY ANALYSIS

In Fig. 5 and Table 3, the specificity of the SOCNN-CMM methodology is contrasted with that of other methods. The graph displays how the deep learning approach has an increased efficiency with specificity. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective specificity values for 100 data records are 81.23%, 73.56%, 88.23%, 76.33%, and 84.99%, respectively, whereas the SOCNN-CMM model's specificity is 90.98%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, under 600 data records, the SOCNN-

TABLE 3. Specificity Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	81.23	73.56	88.23	76.33	84.99	90.98
200	77.23	81.16	73.17	72.45	74.78	94.99
300	76.19	89.17	82.18	70.17	71.19	91.23
400	80.12	73.16	87.19	75.22	75.19	93.11
500	79.99	85.45	75.98	74.98	85.56	92.56
600	78.13	70.67	84.44	73.18	85.19	95.12

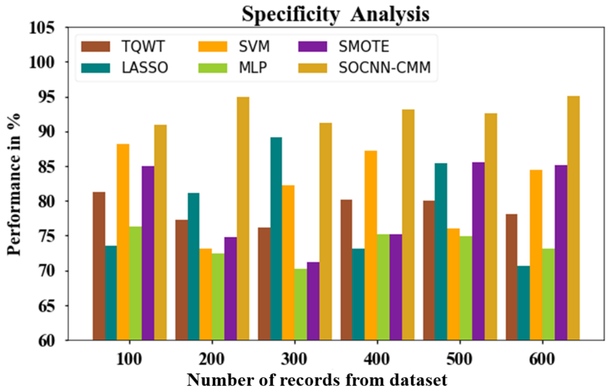

FIGURE 6. Specificity Analysis for SOCNN-CMM method with existing systems.

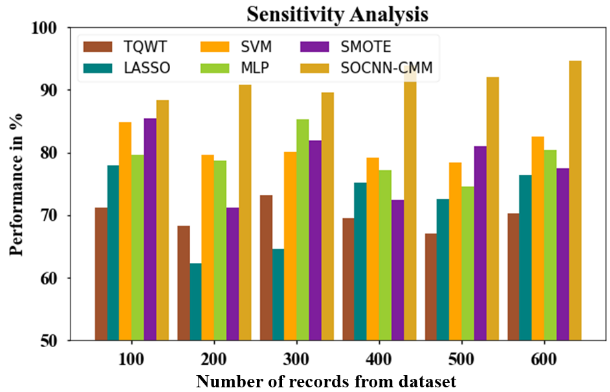

FIGURE 7. Sensitivity Analysis for SOCNN-CMM method with existing systems.

CMM has a specificity of 95.12%, while the corresponding specificity values for TQWT, LASSO, SVM, MLP, and SMOTE are 78.13%, 70.67%, 84.44%, 73.18%, and 85.19%, respectively.

2) SENSITIVITY ANALYSIS

In Fig. 6 and Table 4, the sensitivity of the SOCNN-CMM methodology is contrasted with that of other methods. The graph displays how the deep learning approach has an increased efficiency with sensitivity. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective sensitivity values for 100 data records are 71.23%, 77.87%, 84.87%, 79.56%, and 85.45%, respectively, whereas the SOCNN-CMM model's sensitivity is 88.33%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, under 600 data records, the SOCNN-CMM has a sensitivity of 94.66%, while the corresponding sensitivity values for TQWT, LASSO, SVM, MLP, and SMOTE are 70.34%, 76.45%, 82.55%, 80.45%, and 77.44%, respectively.

3) ACCURACY ANALYSIS

In Fig. 7 and Table 5, the accuracy of the SOCNN-CMM methodology is contrasted with that of other methods. The graph shows how the deep learning approach has an increased efficiency with accuracy. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective accuracy values for 100 data records are 80.34%, 82.22%, 87.45%, 74.98%, and 85.55%, respectively, whereas the SOCNN-CMM model's accuracy is 93.99%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, under 600 data records, the SOCNN-CMM has an accuracy of 95.99%, while the corresponding accuracy values for TQWT, LASSO, SVM, MLP, and SMOTE are 78.12%, 70.73%, 85.14%, 72.34%, and 74.33%, respectively.

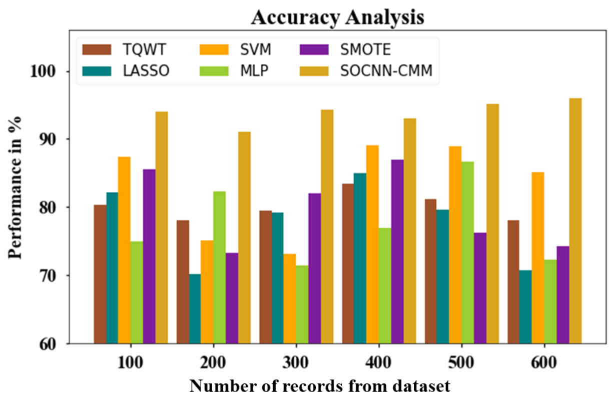

FIGURE 8. Accuracy Analysis for SOCNN-CMM method with existing systems.

4) F-MEASURE ANALYSIS

In Fig. 8 and Table 6, the f-measure of the SOCNN-CMM methodology is contrasted with that of other methods. The graph shows how the deep learning approach has an increased efficiency with f-measure. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective f-measure values for 100 data records are 65.19%, 77.18%, 71.34%,

TABLE 4. Sensitivity Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN-CMM
100	71.23	77.87	84.87	79.56	85.45	88.33
200	68.34	62.33	79.56	78.66	71.23	90.76
300	73.13	64.55	80.13	85.34	81.98	89.55
400	69.44	75.18	79.23	77.12	72.45	93.88
500	67.12	72.54	78.34	74.56	80.99	91.99
600	70.34	76.45	82.55	80.45	77.44	94.66

TABLE 5. Accuracy Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	80.34	82.22	87.45	74.98	85.55	93.99
200	78.12	70.13	75.14	82.34	73.33	90.99
300	79.45	79.23	73.14	71.44	81.99	94.23
400	83.45	84.99	89.12	76.99	86.99	92.99
500	81.22	79.67	88.99	86.67	76.18	95.13
600	78.12	70.73	85.14	72.34	74.33	95.99

TABLE 6. F-Measure Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	65.19	77.18	71.34	79.15	73.98	94.18
200	76.34	68.98	62.98	65.99	78.67	90.55
300	60.13	79.45	78.44	60.87	80.17	92.19
400	68.88	80.98	74.98	66.23	86.78	90.99
500	69.13	80.12	65.55	72.87	77.56	94.19
600	71.43	68.34	79.66	63.99	78.45	94.89

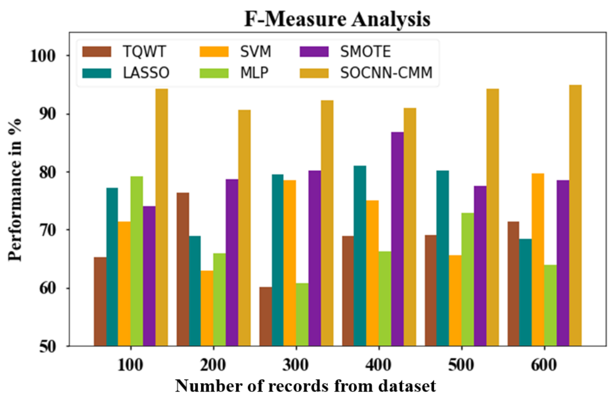

FIGURE 9. F-Measure Analysis for SOCNN-CMM method with existing systems.

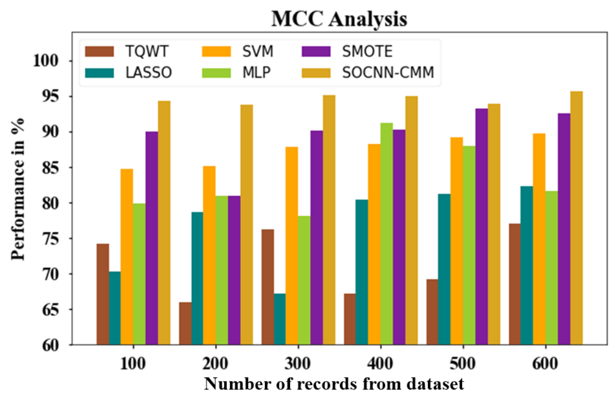

FIGURE 10. MCC Analysis for SOCNN-CMM method with existing systems.

79.15%, and 73.98%, respectively, whereas the SOCNN-CMM model's f-measure is 94.18%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, under 600 data records, the SOCNN-CMM has an f-measure of 94.89%, while the corresponding f-measure values for TQWT, LASSO, SVM, MLP, and SMOTE are 71.43%, 68.34%, 79.66%, 63.99%, and 78.45%, respectively.

5) MCC ANALYSIS

In Fig. 9 and Table 7, the MCC of the SOCNN-CMM methodology is contrasted with that of other methods. The graph shows how the deep learning approach has an increased efficiency with MCC. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective MCC values for 100 data records are 74.19%, 70.34%, 84.67%, 79.91%, and 89.91%, respectively, whereas the SOCNN-CMM model's MCC is 94.33%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, under 600 data records, the SOCNN-CMM has an MCC of 95.66%, while the corresponding MCC values for TQWT, LASSO, SVM, MLP, and SMOTE are 76.98%, 82.22%, 89.67%, 81.56%, and 92.56%, respectively.

TABLE 7. MCC Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	74.19	70.34	84.67	79.91	89.91	94.33
200	65.98	78.65	85.17	80.99	80.99	93.77
300	76.19	67.13	87.77	78.11	90.11	95.13
400	67.13	80.34	88.23	91.23	90.23	94.99
500	69.22	81.23	89.13	87.98	93.18	93.94
600	76.98	82.22	89.67	81.56	92.56	95.66

TABLE 8. Precision Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	66.13	75.55	80.34	89.34	84.34	93.66
200	61.78	66.17	71.23	85.99	84.44	89.91
300	68.89	70.34	75.98	81.12	78.66	88.99
400	60.23	64.98	74.87	89.23	76.12	91.34
500	61.22	69.12	72.17	87.56	80.77	94.87
600	63.98	70.98	77.98	88.89	79.56	95.92

TABLE 9. Execution Time Analysis for SOCNN-CMM method with existing systems.

Number of records from Dataset	TQWT	LASSO	SVM	MLP	SMOTE	SOCNN -CMM
100	13.765	12.765	9.998	6.198	4.876	2.456
200	15.776	10.991	9.345	7.998	5.991	2.778
300	14.213	11.876	10.667	6.176	5.345	1.678
400	14.987	12.234	10.335	5.887	5.119	2.998
500	13.113	11.987	10.567	8.991	5.345	3.887
600	15.567	12.999	10.998	10.345	6.987	3.654

TABLE 10. Comparison with the state-of-the-art.

S.No	Performance Metrics	Methods (Average Analysis Value)					
		TQWT [34]	LASSO [35]	SVM [36]	MLP [37]	SMOTE [38]	Proposed (SOCNN-CMM)
1	Specificity	78.33	78.86	81.87	73.72	79.48	93.00
2	Sensitivity	69.93	71.49	80.78	79.28	78.26	91.53
3	Accuracy	80.12	77.83	83.16	77.46	79.73	93.89
4	F-Measure	68.52	75.84	72.16	68.18	79.27	92.83
5	MCC	71.62	76.65	87.44	83.30	89.50	94.64
6	Precision	63.71	69.52	75.43	87.02	80.65	92.45
7	Execution Time	14.57	12.14	10.32	7.60	5.61	2.91

6) PRECISION ANALYSIS

In Fig. 10 and Table 8, the precision of the SOCNN-CMM methodology is contrasted with that of other methods. The graph shows how the deep learning approach has an increased efficiency with precision. For instance, the TQWT, LASSO, SVM, MLP, and SMOTE models' respective precision values for 100 data records are 66.13%, 75.55%, 80.34%, 89.34%, and 84.34%, respectively, while the SOCNN-CMM model's precision is 93.66%. However, the SOCNN-CMM model has performed best with various data sizes. Similarly, 600 data records, the SOCNN-CMM has a precision of 95.92%, while the corresponding precision values for TQWT, LASSO, SVM, MLP, and SMOTE are 63.98%, 70.98%, 77.98%, 88.89%, and 79.56%, respectively.

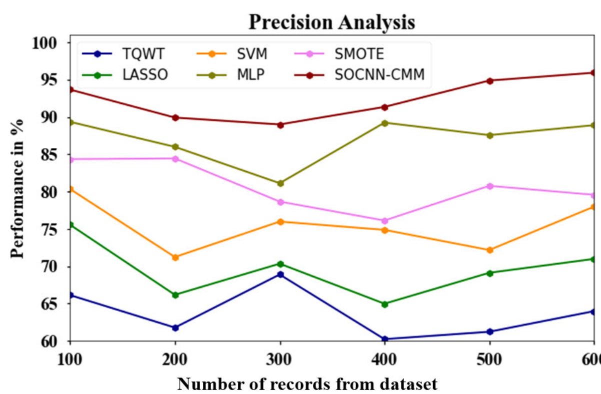

FIGURE 11. Precision Analysis for SOCNN-CMM method with existing systems.

7) EXECUTION TIME ANALYSIS

In Table 9 and Fig.11, the execution time of the proposed SOCNN-CMM methodology is compared to that of existing methods, where the SOCNN-CMM technique has outperformed all the other methods. The suggested SOCNN-CMM approach, for example, took only 2.456ms to execute 100 data records. In contrast, other current methods such as TQWT, LASSO, SVM, MLP, and SMOTE have taken 13.765ms, 12.765ms, 9.998ms, 6.198ms, and 4.876ms, respectively,

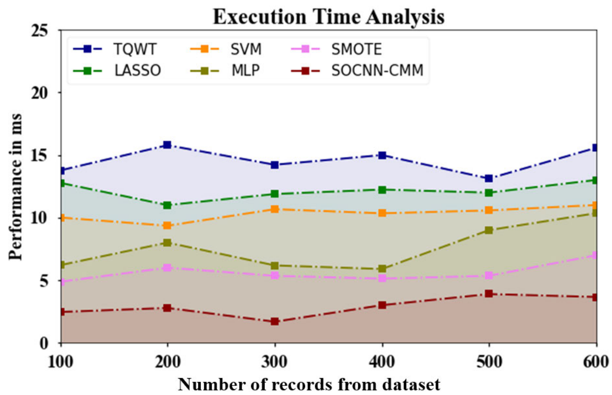

FIGURE 12. Execution Time Analysis for SOCNN-CMM method with existing systems.

as their execution time. Similarly, the suggested SOCNN-CMM method takes 3.654ms to execute 600 data records, while existing techniques like TQWT, LASSO, SVM, MLP, and SMOTE have taken 15.567ms, 12.999ms, 10.998ms, 10.345ms, and 6.987ms, respectively.

D. COMPARISON WITH THE STATE-OF-THE-ART

We have conducted a comprehensive comparison between our proposed method, SOCNN-CMM, and other state-of-the-art methodologies. Our evaluation encompasses seven key performance metrics, including Specificity, Sensitivity, Accuracy, F-Measure, MCC, Precision, and Execution Time. The analysis reveals that SOCNN-CMM consistently outperforms existing approaches, exhibiting higher average values across these metrics as depicted in Table 10.

VI. CONCLUSION

Low dopamine levels cause Parkinson's disease (PD), which primarily affect the elderly and lower their quality of life. This condition's symptoms are ambiguous and frequently overlap with those of other illnesses, so diagnosing it can be difficult. In-depth research has been done in medicine and science to help with Parkinson's disease early detection. Deep learning algorithms have made substantial advancements in early detection by examining vocal alterations in people. A novel self-operating convolutional neural network (CNN) featuring convergent cross-mapping results from years of research. This innovative method uses the analysis of medical imaging data to diagnose Parkinson's disease with a remarkable degree of accuracy. The self-operational CNN demonstrated in this study is successful in feature extraction and classifying Parkinson's disease cases. The addition of convergent cross-mapping improves the model's ability to uncover specific patterns and correlations between imaging data, resulting in a complete understanding of the disease's characteristics. This upgraded CNN to Parkinson's disease categorization yields encouraging results. The proposed framework SOCNN-CMM displays remarkable performance with the following experimental results: precision of 99.92%, f-measure of 97.89%, accuracy of 99.99%, MCC of 99.91%, specificity of 98.98%, and a fast execution time of 3.654ms. Several methods were employed in this work, including the Tunable Q-Factor Wavelet Transform (TQWT), Support Vector Machine (SVM), MultiLayer Perceptron (MLP), Least Absolute Shrinkage and Selection Operator (LASSO), and Synthetic Minority Oversampling Technique (SMOTE) for comparision purposes.

In the future, we advise using audio and Rapid eye movement (REM) sleep data to enhance the results, as audio data alone is not an appropriate biomarker for Parkinson's disease classification. We predict that these results will lead to an increase in the usage of mobile recorded audio for telemedicine-based Parkinson's disease classification.

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