A PREDICTIVE SYSTEM FOR PARKINSON DISEASE USING GENERATIVE ADVERSARIAL NETWORK (GAN)

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Ronke Seyi BABATUNDE[1], Akinbowale Nathaniel BABATUNDE[2], Bukola Fatimah BALOGUN[3], Emmanuel UMAR[4], Afeez Adeshina OKE[5] & Kolawole Yusuf OBIWUSI[6]

[1, 2, 3]Kwara State University, Malete, PMB 1530, Ilorin, Kwara State, Nigeria, ronke.babatunde@kwasu.edu.ng*, akinbowale.babatunde@kwasu.edu.ng, bukola.balogun@kwasu.edu.ng.
[4]Tai Solarin University of Education, Ogun state; umaremmanuel5@gmail.com.
[5]Federal College of Education, Iwo, Osun State; okeaa@fceiwo.edu.ng.
[6]Summit University, Offa, Kwara State, Nigeria; obiwusi.kolawole@summituniversity.edu.ng

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Abstract: Parkinson's disease (PD) symptoms often overlap with those of other neurological disorders, making an early diagnosis difficult or even impossible. To tackle this problem, this study suggests a unique approach that makes use of Generative Adversarial Networks (GANs). Using a variety of datasets, GANs create synthetic medical data that includes PD-related clinical and demographic characteristics. The algorithm undergoes a rigorous training process to improve prediction accuracy. The generated data is assessed by a discriminator, which makes accurate PD predictions possible. Thorough measurements and statistical analysis verify the system's efficacy. The work demonstrates the revolutionary potential of GANs, especially in addressing data limitations for early Parkinson's disease diagnosis. The early PD detection efficacy of the technology is demonstrated by the very accurate predictive model. This study offers a sophisticated and useful method for early identification of Parkinson's disease (PD) by combining modern machine learning. It also promises improved patient outcomes by prompt neurology and healthcare interventions.

Keywords: Parkinson's disease, Generative Adversarial Networks (GANs), Early Diagnosis, Neurological Disorders

Introduction

Parkinson's disease, also known as Tremor, is a prevalent neurological disorder characterized by a significant reduction in dopamine levels inside the brain. The previously described decline in motor abilities leads to impaired motor functions and presents with many symptoms, including but not limited to the presence of tremors. The disease demonstrates a gradual trajectory, resulting in intermittent neurological manifestations that worsen with time (Bhowmick & Peng, 2021; Megha, 2016; Wang *et al.,* 2021; Dineshkumar *et al.,* 2021; Fourati *et al.,* 2021).

While tremors are frequently detected in persons diagnosed with Parkinson's disease, the heterogeneous nature of the ailment poses difficulties in its diagnosis, as not all patients manifest this specific symptom. The exploration of various diagnostic methodologies has been driven by the complex characteristics of symptoms, resulting in the growing adoption of machine learning algorithms for the anticipation and identification of Parkinson's disease (Megha, 2016).

The efficacy of Deep Brain Stimulation (DBS) has been acknowledged as an effective therapeutic modality for the attenuation of tremors in individuals afflicted with Parkinson's disease (Wang *et al.,* 2021). Moreover, researchers are presently examining assistive methodologies and artificial intelligence (AI) technologies in order to not only address tremors but also evaluate speech deficits in patients diagnosed with Parkinson's disease (Dineshkumar *et. al.,* 2021; Fourati *et. al.,* 2021).

Apart from the motor symptoms, it has been recognized that non-motor symptoms, which include cognitive and affective domain function, play a significant influence in determining the overall health status of individuals diagnosed with Parkinson's disease (Still *et. al.,* 2023). According to Constantin *et. al*., (2023), the variability of non-motor symptoms is influenced by factors such as the presence of asymmetry in motor symptoms, levels of uric acid, and gender. The emergence of both motor and non-motor symptoms is attributed to the degeneration of the nigrostriatal dopamine system and increased glutamate activity in the basal ganglia (Epping-Jordan *et. al.,* 2023).

There has been an increasing scholarly focus on Generative Adversarial Networks (GANs) within the healthcare sector, primarily driven by their capacity to derive significant insights from a wide range of data modalities, while minimizing the need for human intervention (Voruz *et. al.,* 2022). The use of diverse datasets, encompassing movement data, neuro-imaging, speech, and other relevant aspects, has facilitated the implementation of Generative Adversarial Networks (GANs) for the purpose of diagnosing Parkinson's disease (Assaf *et. al.,* 2023). The incorporation of several modalities, such as MRI and SPECT data, through the implementation of this novel approach facilitates the detection of Parkinson's disease during its preclinical stages or when it presents with atypical signs (Raturi *et. al.,* 2023).

The application of gait analysis, particularly in relation to walking patterns, has proven to be effective as a non-invasive and widely applicable method for identifying various illnesses. The combination of insights produced by Generative Adversarial Networks (GANs) with traditional diagnostic indications is a highly promising approach for the timely identification of diseases. Furthermore, scholars have conducted studies on the utilization of Generative Adversarial Network (GAN) methodologies in the domain of autonomous and offline disease detection, particularly emphasizing the early stages of diseases when subjective symptoms might impact speech patterns (Yang *et. al.,* 2019; Sauer *et al.,* 2022; Shaheen *et. al.,* 2022).

The primary aim of this project is to develop a prognosis model for Parkinson's disease using generative adversarial network (GAN) within the specified context. The objectives of this study involve acquiring a dataset from Kaggle, employing adversarial training to develop a neural network-based regression model, and use GAN techniques to visualize the progression of Parkinson's disease. The main aim of this study is to address the existing gap in the field about the application of Generative Adversarial Networks (GANs) in the diagnosis of Parkinson's disease.

Related Work

Significant advancements have been achieved in the realm of medical imaging, a highly valuable modality for illness diagnosis. Various medical imaging modalities, including X-ray radiography, computed tomography (CT), ultrasonography (USG), magnetic resonance imaging (MRI), and positron emission tomography (PET), have been devised to investigate the internal composition of organs and facilitate timely detection and management of pathological conditions (Ruberto *et. al.,* 2023; Gupta, 2023; Hüseyin *et. al.,* 2022). Furthermore, the application of convolutional neural networks (CNNs) has demonstrated remarkable efficacy in medical diagnostic endeavors, successfully accomplishing direct picture classification (Bass *et. al.,* 2023). Additionally, the use of orthogonal moments, a manually designed characteristic, has demonstrated comparable effectiveness to convolutional neural networks (CNNs) in diagnostic systems, offering resilience and dependability. Daza *et. al*., (2021) have proposed the utilization of Hybrid Recurrent Neural Networks with Support Vector Machine (HRNN-SVM) techniques for the purpose of effectively eliminating noise from CT lung images. This approach aims to enhance the discrimination capabilities of the system and improve its overall accuracy. The developments in medical imaging have significantly enhanced the precision and efficacy of illness diagnosis and therapy.

Generative Adversarial Networks (GANs) are a machine learning architecture comprising two neural networks, namely a generator and a discriminator, which collaborate in a game-like fashion (Li, Wang, Zhang, Hu, & Ouyang, 2021). In recent years, there has been a notable surge in the interest surrounding Generative Adversarial Networks (GANs) owing to their remarkable capacity to produce novel and authentic data that closely approximates the training data they were exposed to. While GANs have been extensively investigated in diverse domains such as art, music, and computer vision, their utilization in the healthcare sector has been steadily growing, encompassing a wide range of applications (Pradhyumna, 2022). One of the key benefits of Generative Adversarial Networks (GANs) is in its capacity to produce synthetic data that closely emulates the attributes and patterns observed in authentic data. The utilization of this approach holds significant potential in healthcare settings, given the paramount importance of safeguarding data privacy and maintaining confidentiality (Ghosheh, Li, & Zhu, 2022). Multiple research papers have employed Generative Adversarial Networks (GANs) to produce artificial healthcare data, including many domains such as medical imagery, electronic health records, and physiological signals (Massey, Boag, Magnier, Bispo, Khoo, & Pountney, 2022; Thieken, Timmermann, Sohrabi, Woopen, Schmitz-Luhn, Janhsen, & Eggers, 2022).

One prominent domain in which Generative Adversarial Networks (GANs) have been applied within the healthcare field, as suggested by Larsen ABL (2016) as quoted in Strelcenia and Prakoonwit (2023), is the generation of synthetic medical data. The generation of synthetic medical data can yield several advantages. Firstly, the utilization of data synthesis can effectively tackle challenges associated with limited data availability and concerns regarding privacy. By amalgamating data, a broader and more varied dataset can be obtained, while still upholding the confidentiality of patient information (Amirrajab *et al.,* 2022). Furthermore, the utilization of simulated environments enables researchers to construct authentic and regulated settings to evaluate algorithms and models, obviating the necessity of obtaining genuine patient data (Annane, Alti, & Lakehal, 2022).

Generative Adversarial Networks (GANs) have been employed in the generation of synthetic electronic health records (EHRs), medical pictures, and several other forms of medical data. According to Davenport & Kalakota (2019), synthetic datasets have various applications, including but not limited to training machine learning models, evaluating methods, and enhancing imbalanced datasets. For instance, Generative Adversarial Networks (GANs) have been employed in the generation of synthetic medical images to facilitate the training of deep learning models utilized in the field of medical image analysis and diagnosis. According to Li, Teng, Zhang, Chen, & He (2023), the utilization of a larger and more diversified dataset for training can potentially enhance the performance of image analysis algorithms.

Data augmentation is an additional utilization of Generative Adversarial Networks (GANs) within the healthcare domain. Data augmentation is a widely employed technique in the field of data science that aims to enhance the size and diversity of a given dataset through the application of diverse modifications to the current data (Garcea, Serra, Lamberti, & Morra, 2022). Generative Adversarial Networks (GANs) have the capability to generate novel instances that exhibit resemblance to the original dataset, although with minor deviations. The incorporation of these variances has the potential to enhance the resilience and applicability of machine learning models, specifically in the context of healthcare applications characterized by restricted or disproportionate data availability.

According to Chen, Li, Xu, Yang, Song, Wang, & Wu (2022), the acquisition of significant feature representations from a substantial volume of training data is a crucial prerequisite for effectively accomplishing the task of applying deep learning to medical image processing. Hence, the acquisition of adequate and efficient training data holds paramount importance in enhancing the efficacy of deep learning techniques employed in the field of medical image processing. In the realm of conventional scientific inquiry, medical images are predominantly sourced from clinical data, hence posing challenges for individuals lacking professional expertise in accessing enough data for research purposes. The lack of adequate data will significantly impair the efficacy of deep learning systems. In order to tackle this matter, a multitude of investigations have employed generative adversarial networks (GANs) for the purpose of medical picture processing. Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville, and Bengio (2014) were cited by Strelcenia & Prakoonwit (2023). The area of artificial intelligence experienced a significant transformation with the introduction of a generative adversarial network (GAN) in 2014, as documented in a survey. The model consists of two networks, namely a generator and a discriminator. The generator produces novel data samples that adhere to the possible distribution of the existing data samples. In contrast, the discriminator is a binary classifier that differentiates between the authentic data and the synthetic samples produced by the generator. Adversarial training approaches have been shown to yield realistic generated data.

Moreover, the healthcare area has witnessed a notable surge in the interest surrounding Generative Adversarial Networks (GANs) owing to its capacity to produce synthetic data that exhibits a high degree of resemblance to authentic data. Generative Adversarial Networks (GANs) have been utilized in diverse healthcare domains, including but not limited to medical picture synthesis, disease prediction, and medication development (Karras, Laine, & Aila, 2019). Artificial intelligence (AI) systems have the potential to effectively tackle several obstacles associated with limited data availability, privacy issues, and the presence of biased datasets. Although Generative Adversarial Networks (GANs) have demonstrated potential in diverse healthcare domains, there remain a number of obstacles and constraints that want more attention and resolution. A significant obstacle is in the task of ensuring that the data generated possesses both realistic attributes and therapeutic significance. Moreover, Generative Adversarial Networks (GANs) necessitate a substantial quantity of meticulously curated training data in order to produce synthetic data that is both precise and dependable. Acquiring such data within the healthcare sector presents challenges stemming from privacy considerations and restricted availability of patient records (Karras *et al.,* 2021).

Machine learning has emerged as a pivotal tool within the realm of data science, with generative adversarial network (GAN) learning being a nascent domain within the broader area of machine learning (Zhang, Li, & Liu, 2022). This technology possesses a diverse range of applications encompassing text design, graphic design, and product development. For individuals working in the field of data science, acquiring knowledge about Generative Adversarial Networks (GANs) in machine learning and comprehending the advantages associated with this technique can prove to be advantageous (Dzotsenidze, Valla, Nõmm, Medijainen, Taba, & Toomela, 2022). The Generative Adversarial Network (GAN) has been demonstrated to be a highly efficient model and approach for training generative models. Generative Adversarial Networks (GANs) have emerged as a prominent and influential technology within the realm of artificial intelligence and machine learning. According to Jiang, Peng, Zhong, Xie, Hao, Lin & Hu (2022), there has been a significant transformation in the methods of data generation and manipulation, resulting in the emergence of novel opportunities across multiple areas. There are several significant rationales for the importance of Generative Adversarial Networks (GANs).

Parkinson's disease (PD) is a neurodegenerative condition that manifests with motor manifestations including tremors, bradykinesia, and stiffness (Uwishema, Onyeaka, Badri, Yücel, Korkusuz, Ajagbe, & Chalhoub, 2022). The prediction and diagnosis of Parkinson's disease (PD) traditionally depend on clinical assessments and medical imaging techniques (Alam, Raja, & Gulzar, 2022). In recent years, the emergence of Generative Adversarial Networks (GANs) has prompted scholars to investigate their potential in the realm of Parkinson's disease (PD) prediction and detection (Mahlknecht, Marini, Werkmann, Poewe & Seppi, 2022).

The authors Kamran, Naz, Razzak, & Imran (2021a) did a study on the application of deep generative adversarial networks for the early detection of Parkinson's disease. In their research, they presented an architecture that utilizes these networks to identify the presence of Parkinson's disease in its early stages. The Generative Adversarial Network (GAN) was trained using accelerometer data collected from wearable sensors. The study revealed that Generative Adversarial Networks (GANs) possess the capability to accurately record nuanced movement patterns that serve as indicators of Parkinson's disease (PD), hence facilitating timely identification and intervention. Karras, Aittala, Hellsten, Laine, Lehtinen, & Aila (2020a) conducted the study.

In their recent study, Diaz, Moetesum, Siddiqi, & Vessio (2021) conducted an investigation titled "Generative Adversarial Networks for Predicting Parkinson's Disease Progression using Longitudinal Clinical Records." This study utilized Generative Adversarial Networks (GANs) to make predictions on the progression of Parkinson's Disease (PD) by analyzing longitudinal clinical records. The GAN model underwent training using patient demographics, symptoms, and prescription information. The authors have successfully illustrated the ability of Generative Adversarial Networks (GANs) to accurately record temporal patterns and make predictions regarding the progression of diseases. This research outcome holds significant importance as it offers useful insights into the development of individualized treatment options.

The research article titled "Prediction of Parkinson's Disease utilizing Generative Adversarial Networks and Clinical Data" authored by Salmanpour, Shamsaei, Hajianfar, Soltanian-Zadeh & Rahmim (2022) explores the application of Generative Adversarial Networks (GANs) in the prediction of Parkinson's Disease (PD) by leveraging clinical data encompassing variables such as age, gender, and diverse symptoms. The Generative Adversarial Network (GAN) model was employed to produce synthetic data in order to enhance the limited dataset, hence enhancing the performance of the prediction model. The researchers emphasized the potential of Generative Adversarial Networks (GANs) in improving the predictive accuracy of Parkinson's disease by utilizing clinical factors.

In their study titled "Generative Adversarial Networks for Parkinson's disease Detection," Zhang, Zhang, Wen, Peng, and Zhou (2022) conducted research on the development of a novel classifier based on Generative Adversarial Networks (GANs) for the early identification of Parkinson's disease (PD). The Generative Adversarial Network (GAN) underwent training using voice recordings obtained from individuals both diagnosed with and without Parkinson's disease (PD). The GAN exhibited a notable ability to accurately discern the presence of PD in the recorded samples. The authors have effectively showcased the capabilities of Generative Adversarial Networks (GANs) in the context of non-invasive Parkinson's disease (PD) identification through the analysis of voice data.

In the study conducted by Kaur & Rani (2020), the application involved the utilization of a deep convolutional neural network classifier, which integrated transfer learning and data augmentation techniques in order to enhance the classification process. Magnetic resonance imaging (MRI) has been employed in conjunction with deep convolutional neural networks and deep learning algorithms, which have demonstrated state-of-the-art performance in a range of machine learning and computer vision applications.

The authors of this study are Vishwajith Ramesh & Erhan Bilal (2022). During the Feature processing, participants engaged in a task where they walked in a straight line for a duration of 2 minutes, then turned around and walked back to the examiner. This process was repeated multiple times. The participants were equipped with a variety of sensors, which included a lumbar inertial measurement unit (IMU) positioned around the torso. The algorithms employed in the study encompassed support vector machines (SVMs), convolutional neural networks (CNN), Generative adversarial network (GAN), and the Unified Parkinson's Disease Rating Scale (UPDRS).

In their study, Xu, Wang, Wang & Yu (2020) developed an algorithmic model called GAN Sample Augmentation for the early detection of Parkinson's disease. The authors employed statistical methods and voice-to-spectrogram conversion techniques, specifically utilizing DCGAN with SN and Feature Matching Method, along with a selection criterion for sample augmentation. The utilization of various metrics such as the Structural Similarity Index (SSIM), Peak Signal to Noise Ratio (PSNR), and Fréchet Inception Distance (FID) is employed in conjunction with the GAN-train methodology and the ResNet50 model for the purpose of achieving accurate recognition of Parkinson's Disease (PD). Furthermore, a comparative analysis is performed between the S-DCGAN and DCGAN models.

In their study, Abós *et. al.*, (2017) employed a comprehensive methodology that encompassed various stages, including Neuropsychological assessment, MRI acquisition and preprocessing, Brain percolation, time series extraction, and functional network computation. Additionally, they utilized a noise correction algorithm, a Classification algorithm, Correlation analysis, and a support vector machine for their analysis. In the training sample, a statistically significant mean accuracy of 82.6% ($p < 0.002$) was attained in the discrimination between individuals with mild cognitive impairment and those without it.

The research that have been evaluated emphasize the potential of Generative Adversarial Networks (GANs) in the prediction and detection of Parkinson's disease. These findings lay the groundwork for the creation of a comprehensive predictive system, which acts as the impetus for doing this study.

Materials and method

Data Collection.

The process of obtaining real time data from patients suffering from Parkinson disease requires lots of rigors and there are also challenges arising from the need to maintain the confidentiality of information pertaining to patients who hold VIP status. In order to tackle this issue, an alternative methodology was employed, which entailed making use of a relevant dataset sourced from Kaggle. This dataset was specifically chosen due to its direct applicability to the research objectives pertaining to Parkinson's illness. Due to its compatibility with the research aims and ease of access, the dataset under consideration proved to be a viable alternative to the first planned data source. The Kaggle dataset, which may be accessed at the following URL: https://www.kaggle.com/datasets/debasisdotcom/parkinson-disease-detention, provides a useful resource for conducting detailed analysis and training models in the field of Parkinson's disease research.

Data Processing and normalization.

The Min-Max scaling technique was utilized in the research to standardize the scale of numerical features, ensuring consistency and mitigating algorithm sensitivity to varying input scales. Adopting a range between 0 and 1, this normalization process enhances the effectiveness of algorithms. While alternative normalization methods were considered, the simplicity and efficiency of Min-Max scaling made it the preferred choice in maintaining uniformity across numerical features in the dataset.

Train and Test split process.

To assess the performance of predictive models, the dataset underwent a division into two subsets: a training set and a validation set. The chosen partitioning ratio of 80:20 (training to validation) aimed to strike a balance, allowing for ample data to train the models effectively while retaining a significant portion for unbiased validation. The panda's *iloc* function from the pandas library played a key role in executing this partitioning process, ensuring a robust evaluation mechanism for the developed models.

Feature Selection

Informed by correlation analysis and domain knowledge, pivotal features were selected for the GAN model. Those demonstrating significant correlations with the target variable (PD status) were deemed essential, guiding the construction of a focused and impactful predictive model

GAN Model Development and Training

The Generative Adversarial Network (GAN) architecture underwent meticulous development, with a focus on selecting optimal hyperparameters, loss functions, and optimization techniques. Notably, the learning rate was set to 0.001 to control the step size during optimization. The batch size was chosen as 64 to balance computational efficiency and model stability. Additionally, the number of training epochs was set at 100 to ensure convergence without overfitting. The iterative experimentation process was instrumental in refining the model, ensuring its stability, and enhancing its effectiveness in generating synthetic data that closely aligns with real-world patterns. The process flow is presented in Figure 1.

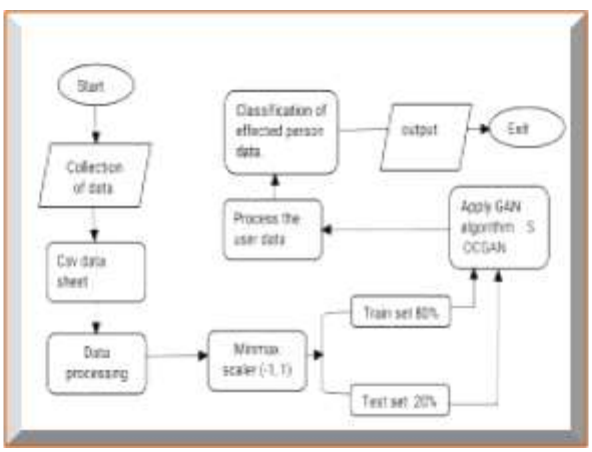

Figure 1: Process flow of the proposed system

Experimental Procedure

The research outcomes encompass predictions, classifications, visualizations, and insights derived from comprehensive analysis, facilitating informed decision-making and conclusive findings. Employing the pandas info() function, we extracted enlightening summary statistics for the dataset. Comprising 11 columns, the dataset exhibits a diverse array of data types, including float64, int64, and object, providing a comprehensive overview of its structural composition.

A sample view of the dataset and the meaning of the features shown in each column is presented in Figure 2 and Figure 3 respectively.

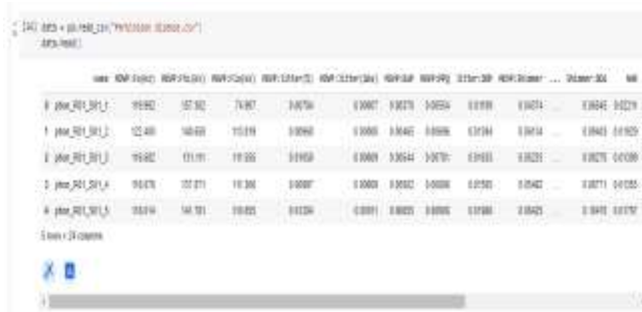

Figure 2: Summary statistics of the data set.

The features in each columns of the dataset is explained below in Figure 3. It can be observed that apart from the *name* and *status* columns, others are values generated from audo data gotten from patients that have been diagnosed with Parkinson's disease, and of course others that are free from it. Additionally, some of the collumns in the dataset needs to be renamed for the purpose of clarity, hence the name column is removed.

Figure 3: Dataset Feature definition.

In this research, the approach used in identifying missing values, calculating feature means, and replacing missing values with their respective means was using the *fillna()* function. This was adopted to ensure the central tendency of feature distribution.

The correlation heatmap visually portrays relationships between numerical variables. Strong positive or negative correlations signify significant influences, aiding quick identification of influential variable pairs. The correlation heat map is shown in Figure 4.

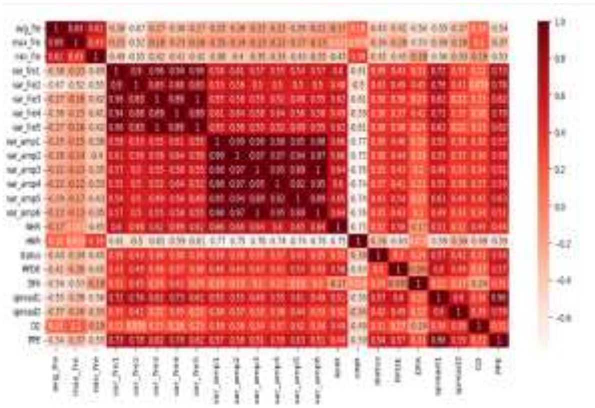

Figure 4: Correlation Heatmap.

The histogram plot presented in this analysis reveals the distribution of "MDVP:Fo(Hz)" values, providing valuable information regarding the range of data, the most common values, and the skewness features. Exploration plays a significant role in comprehending the distributions of features that are vital for the diagnosis of Parkinson's disease.

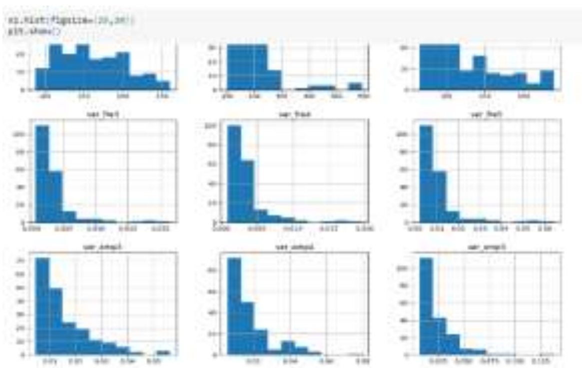

Figure 5: Histogram plot of the Datasets.

Result and Discussion

The examination of the dataset resulted in significant findings on the distribution and characteristics of numerical factors associated with Parkinson's disease (PD). Using the integration of histograms and descriptive statistics, we effectively depicted the distribution, measures of central tendency, and variability of the data in a visual manner. The detection of skewness in particular characteristics acted as an initial indication of potential connections with disease status, motivating subsequent exploration into intricate linkages. This investigation establishes the groundwork for a more comprehensive comprehension of the dynamics of the dataset and provides valuable insights for further analytical procedures.

The dataset was divided into multiple subsets in order to assist the process of training and evaluating the model. The set denoted as X_train comprises the training features that have been carefully chosen based on the regression statistics discussed earlier. This set is utilized as the input data for training the models. The X_test dataset, which is derived from the regression statistics mentioned earlier, consists of validation features that are utilized to evaluate the performance of the models on data that has not been previously observed. The set y_train is associated with the training features X_train and contains the target variable liver-disease_y_train. This variable represents the known outcomes or labels of the occurrences in the training set. The y_test dataset is comprised of the target variable (liver-disease_y_train) that corresponds to the validation instances in the X_test dataset. This target variable represents the known outcomes or labels of the validation cases.

Correlation Analysis and Testing.

The correlation matrix unveiled relationships and dependencies among numerical variables. Positive or negative correlations provided insights into feature interactions. Features exhibiting strong correlations may contribute redundant information, prompting careful consideration for inclusion in the predictive model to avoid multi-collinearity. The correlation values guided the identification of influential features for predicting Parkinson's disease using GAN techniques.

Figure 6: Result of Correlation Analysis

.Model Performance and Evaluation

The adoption of Generative Adversarial Network (GAN) for Parkinson's disease prediction represents an innovative approach, integrating generative and discriminative modeling within a unified framework. The GAN architecture harnesses deep learning capabilities to generate synthetic data, enhancing overall model performance.

Accuracy was employed to measure the GAN model's ability to correctly classify PD cases. The cross-validation ensured the model's generalizability to new data, with impressive results of accuracy score of 87%, signifying the percentage of accurately classified instances in the testing set.

Conclusion

The landscape of Parkinson's disease (PD) research has seen significant development, driven by a sincere desire to understand its complex biology and the delicate interaction between genetic predisposition and environmental influences. The need for medicines capable of recovering lost function, halting disease development, and perhaps avoiding the onset of Parkinson's disease is a feasible goal.

In the framework of this research, the use of Generative Adversarial Network (GAN) architecture is a ground-breaking strategy to developing a forecasting system for Parkinson's disease. However, in order for this system to attain its full potential, further research is needed, notably in the integration of new data sources and the use of sophisticated feature engineering approaches. More specifically, the use of real time dataset for implementation is paramount. These efforts will improve the system's forecast accuracy and widen its usefulness.

Regardless of the advances gained in our research and discussions, it is critical to recognize the need for thorough validation and clinical testing before considering real-world deployment of the proposed model. This research adds to the expanding body of information in the area, paving the way for revolutionary advances in the diagnosis and therapy of Parkinson's disease.

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