CHATPER 8

CONCLUSION AND FUTURE WORK

8.1. CONCLUSION

The first contribution of the work introduces fuzzy convolution long short-term memory-based convolutional neural networks (FCLSTM-CNNs), which extract feature representation directly from the concatenation of several characteristic sets. This method is known as feature-level combination. For this reason, a framework based on FCLSTM-CNN is designed, which helps us differentiate between people with Parkinson's disease and healthy persons. A few features are taken out of the input dataset in order to use them in PD classification. Reducing the dimensionality of features is accomplished through the utilization of kernel principal component analysis (KPCA). From the complete features collection, informative characteristics are chosen using the minimum Redundancy Maximum Relevance (mRMR). Features with high relevance scores are chosen using mRMR and redundant features are removed using this, in accordance with the class label. Finally, an FCLSTM-CNN classifier is used to carry out the classification. The most popular Feature Selection (FS) method in use today is the metaheuristic methodology. Fuzzy Monarch Butterfly Optimization Algorithm (FMBOA) can be used to expand this for features selections.

The work's second contribution is the development of deep fuzzy convolution bi-directional long short-term memory (FCBi-LSTM) classifiers for the classification of Parkinson's disease based on speech data. Several features from the database, such as TQWT, Wavelet, MFCC, and Concat, have been retrieved in order to classify the dataset for PD detection. The input dataset is where this process starts. Based on the recovered features, dimensionality reduction based on KPCA is applied to the input dataset. Significant features are selected from the dataset and redundant features are eliminated using an FMBOA-based feature selection method. Original features are given feature weights based on how important they are to the classification goal utilizing the FMBOA-based selection of features approach. Following that, the traits with the highest weights are selected for categorization. The FCBi-LSTM classifier then modifies the Parkinson characteristics retort and computes the fuzzy weight using the function of membership in order to identify the viable features of the discovered characteristics. A suggested classifier automatically and directly creates feature representations by use of parallel convolution layers linked to each set of features. To determine the connection between the characteristics and predict them sequentially, the FCBi-LSTM classification is utilized. Techniques for Ensemble Feature Selection (EFS), which increase the stability of the FS process, have been included to the work.

The third part of this research effort introduces FCBi-LSTM and optimization-based ensemble feature selection (OBEFS) for PD analysis. The FMBOA, adaptive firefly algorithms (AFA), and levy flight cuckoo search algorithms (LFCSA) are a few of the algorithms upon which the proposed OBEFS method is predicated. The best characteristics from each of the three feature subsets are selected using OBEFS, which is based on correlation function. Under FCBi-LSTM classifier, PD diagnosis is then presented. Patients with Parkinson's disease can benefit from early diagnosis made possible by the accurate and effective model, which also helps doctors treat and recover from their patients.

The work's last contribution, an ensemble deep-learning (EDL) classifiers that incorporates individual methods, is proposed together with OBEFS. Proposed and implemented, OBEFS relies on algorithms such as FMBOA, LFCSA, and AFA. To select the top features from each of the 3-feature subsets, OBEFS uses the correlation function. Next, FCBi-LSTM, CAE, and SAE were added in the EDL classifier. The purpose of the layered generalization is to aggregate the output of classifiers that only select the dataset's majority class. The ML repository at the University of California-Irvine (UCI) is utilized to test several classification strategies, and the results are assessed using the MCC, f-measure, accuracy, and error metrics. The purpose of the layered generalization is to aggregate the output of classifiers that only select the dataset's majority class. Based on the final feature level combination, the results demonstrate that the suggested classifier provides higher accuracy results of 99.903%, while other approaches like SVM, CNN, FCLSTM-CNN, and FCBi-LSTM yield accuracy findings of 88.1294%, 94.1752%, 95.1557%, and 98.7720%, respectively.

8.2. FUTURE WORK

Future studies could explore the use of sampling techniques, such as over sampling or under sampling, to balance the datasets. Improving performance and eliminating the bias against the majority class would both benefit from this. Particular datasets were used in the current study's model building and assessment. In order to evaluate the produced models' robustness and generalizability, future research may test them on external datasets or actual data. This would provide light on how well the suggested techniques work with various populations and how applicable they are in real-world scenarios. We can improve the field of Parkinson's disease (PD) identification using voice data and aid in the creation of precise, dependable, and therapeutically useful diagnostic instruments by tackling these prospective research areas.