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Implementation of Intelligent Deep Learning Approach for Multiple Class Stress Identification by using Observed Variable Heart Signals

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ABSTRACT

Stress is a one of the crucial physiological and psychological features that shows more impact on health conditions of person and also shows impact on life style. Most of the conventional stress evaluation approaches are depends on individual matters, fail to monitor continuous data samples and deviated the predictions, mostly these approaches focused on binary classification and not supporting multiple classification. In this research we Implementation of Intelligent Deep Learning Approach for Multiple Class Stress Identification by using Observed Variable Heart Signals (IDLMCSI) approach, Variability in heart rate is gathered in the form of HRV signals through IoT wearable devices, dynamic data samples are processed using feature engineering approaches and then apply 1D CNN to learn features that belonging to stress, identified various kinds of stress movements and classified into various types classes. Performance of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits high percent of accuracy, high percent of recall, high percent of F1-score, and high percent of precision due to optimization of functions and as well as supporting convolutional FL approach, proposed IDLMCSI exhibits low value of log loss and that represents more accurately predict classes with high confidence value, exhibits high value of Cohen's Kappa and exhibits high value of MCC due to optimization of functions and as well as supporting convolutional FL approach.

1. INTRODUCTION

Stress is a one of the common problems in our daily life, heavy pressure from profession, job of completion with in time period, societal roles and responsibilities, and related features of surroundings [1]. The stress due to time limit can improve preparedness and mental conditions, the stress which is not possible to manage may automatically create lot of impact on human health issues like depression stage, increase nervousness, collapse of immune system, disorders in cardiovascular, and optimized the decision-making skills [2]. As a consequence, stress is treated as psychological feature and as well as creates important health hazard, and that shows the importance of identification of stress related issues at early stages by continuously observing human's health conditions [3].

Traditional stress evaluation and management approaches are mostly depending on counseling queries, level of psychological features, and observing responses by raising some questions [4]. All these kinds of approaches facilitate useful information but there is a possibility of deviations from person to person, destruction of normal memory functions, and not in a position to recognized physiological answers for certain questions [5]. In addition to that all these evaluation approaches are not appropriate for monitoring and observe patient's health conditions continuously and fail to deploy in the real time to observe patient's health situations time to time [6].

The day by day advances in technology in the market many wearable IoT devices are available to monitor continuously and gather stress related signals from patient's body [7]. From the list of these signals HRV (variability in heart rate) is one among them and it is used to analyze patients stress variation levels automatically due to it is directly connected with human's nervous functionalities [8]. HRV feature imitates over parasympathetic answers and concerned answers, and it can be approved as a one of the important measures to decide physiological changes due to stress variations [9].

Optimized HRV is generally observer with different conditions of stress levels, high value of HRV shows healthy and relaxed situations, and low value represents high impact on health conditions [10]. With advanced developments in AI, ML, and DL approaches may use to analyze automatically patient's physiological features through signals [11]. These techniques facilitate different types of models to identify various kinds of relationships in physiological features with help of HRV signals and produced better results than conventional approaches [12]. Many of the conventional stress management approaches are classify data samples based on binary classification, and classify data samples into either stressed or relaxed. The changes in the environment binary classifications may miss some of the important features and may not be suitable to deploy into real-time to observe patients stress levels.

All these problems are motivated to Implementation of Intelligent Deep Learning Approach for Multiple Class Stress Identification by using Observed Variable Heart Signals (IDLMCSI) approach, Variability in heart rate is gathered in the form of HRV signals through IoT wearable devices, dynamic data samples are processed using feature engineering approaches and then apply 1D CNN to learn features that belonging to stress, identified various kinds of stress movements and classified into various types classes. Proposed method exactly suitable to apply under dynamic environment with different conditions and that can be used to effectively monitor and observer patients stress levels.

2. LITERATURE REVIEW

Authors in [13] described an approach that can be able to identify relationship over HRV signals and human stress level, discussed how the stress rapidly changes and collapse entire human nervous system, they used HRV is a prime measure to decide human stress level, proved HRV values are low under stress situations and experiments conducted with static data samples but not appropriate for dynamic samples. Authors in [14] followed standard medical policies to measure HRV values and then analyze the stress level of patients, shows the importance of frequency HRV related and time HRV related features, the complete analysis for stress values is based on HRV parameter, authors calculated stress value based on statistical approaches but they are not adopted any modern AI methods to automatically analyze stress level.

Authors in [15] elaborated a new stress evaluation approach based on HRV signals with help of conventional ML techniques, shows medium level accuracy in detecting stress features, their approach shows less scalability and less robustness. Authors in [16] used conditional data samples for measurement of stress especially in knowledge engineers, studied stress level with constraints like various kinds of interruptions and pressure with different time intervals, worked with multiple class stress measuring technique but shows medium level performance due to excessive training of data samples. Authors in [17] represented stress identification approach by using HRV signals and physiological signals, they discussed how stress outcome influences changes in cardiovascular features under various types of constraints, authors used set of rules and as well as statistical measures to classify stress levels but it is not suitable to handle stress signals with heavy complexity.

Authors in [18] worked on stress identification technique with help of HRV signals that are discovered from IoT based wearable devices, analyzed stress signals by using various kinds of ML techniques, discussed how wearable devices helpful in monitoring stress level in human body, for static data samples their model exhibits moderate performance but when applied to unseen data sample the model degrade or show less accuracy, and not capable to handle continuous data samples. Authors in [19] discussed stress measuring approach to handle continuous data samples with physiological features that are gathered discovered from IoT based wearable devices based on every day wearables cases, analyzed stress signals by using various kinds of statistical techniques, tried to analyze HRV signals under real time cases, and their model working with static data but not used any learning approaches to study stress conditions.

Authors in [20] introduced ensemble learning approach to identify stress level in human body using HRV signals, exhibits moderate performance when compared with statistical stress measurement approaches, accepting data samples with small size and takes lot of time to identify appropriate features, and not suitable to handle data samples with large size. Authors in [21] conducted detailed study on physiological features related to human body stress under various kinds of work with different conditions, HRV signals are studied under various types of mental conditions, the study described the how stress is modifying based on changes with HRV signals but there are not adopted any modern technique to automate analysis for stress management.

Authors in [22] elaborated a new stress measurement approach with help of HRV signals by combining neural networks and features related to frequency of HRV signals, they shown how their approach enhanced accuracy of classification, worked with binary classification but limited to handle continuous dynamic data samples. Stress is a one of the common problems in our daily life, heavy pressure from profession, job of completion with in time period, societal roles and responsibilities, and related features of surroundings. All these kinds of approaches facilitate useful information but there is a possibility of deviations from person to person, destruction of normal memory functions, and not in a position to recognized physiological answers for certain questions.

The stress due to time limit can improve preparedness and mental conditions, the stress which is not possible to manage may automatically create lot of impact on human health issues like depression stage, increase nervousness, collapse of immune system, disorders in cardiovascular, and optimized the decision-making skills. After complete research survey we identified list of gaps that are Many of the previous works on stress management focused on binary classifiers to classify stress level into two classes and it not sufficient to analyze complete picture of variation of stress in human body, only few members are worked on multiple class stress identification approach to handle HRV signals, and conventional ML techniques are not appropriate to handle HRV signals completely. These limitations show the necessity of intelligent stress identification approach to measure complete picture of HRV signals.

3. IDLMCSI STRESS PREDICTION MODEL

In this research we Implementation of Intelligent Deep Learning Approach for Multiple Class Stress Identification by using Observed Variable Heart Signals (IDLMCSI) approach, Variability in heart rate is gathered in the form of HRV signals through IoT wearable devices, dynamic data samples are processed using feature engineering approaches and then apply 1D CNN to learn features that belonging to stress, identified various kinds of stress movements and classified into various types classes. Experiments are connected with help of HRV signals which are gathered directly from medical labs and dynamic data samples through wearable IoT devices. The dataset has recordings of physiological signals (ECG signals) and these are taken from patients under different types of stress conditions.

Gathering of physiological signals (ECG signals) are collected at different point of intervals, RR Interval and R-Peak Generation, apply feature engineering to construct sequence of HRV values from RR signals to observe nervous system functionality, normalized values are rearranged into 1D tensor that are appropriate for CNN approach, the tensor values are applied to convolution filtering process for feature learning, apply Pooling approach to reduce dimensions in the features, the pooled values are aggregated to map into 1D feature vector, optimized entropy loss for optimizing model, measured final stress values and classified as zero represents no stress class, one represents moderate stress, and two represents heavy stress. The complete architecture of proposed Identification by using Observed Variable Heart Signals (IDLMCSI) approach are visualized in Figure 1.

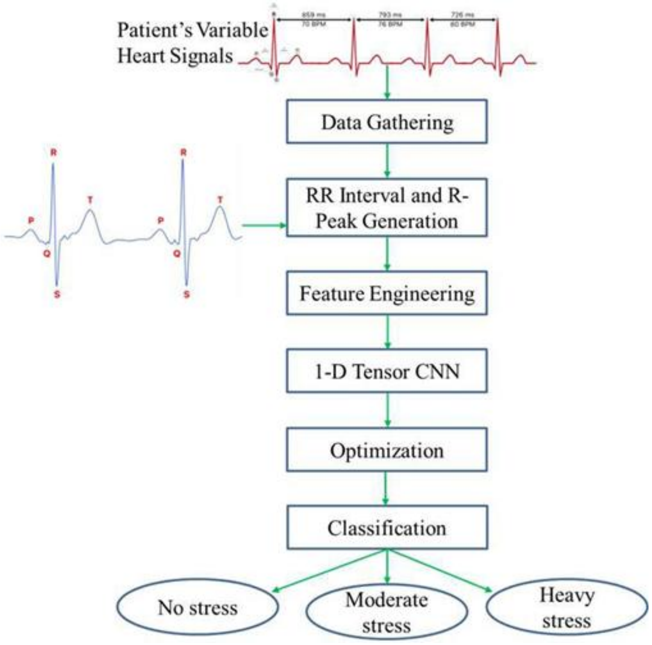

FIGURE 1. Architecture of Proposed IDLMCSI Approach

Step 1: Gathering of physiological signals: ECG signals are collected at different point of intervals as $S_{ECG}(t)$, $t \in [0, R_t]$, $R_t$represents total time of signal recoding. The ECG signals applied to sampling using frequency (f_{ECG}) to generate discrete signals with time as $S_{ECG} = S_{ECG} \frac{j}{f_{ECG}}, j = 1,2, \ldots$

Step 2: RR Interval and R-Peak Generation: From $S_{ECG}[n]$, the values of R-peak is evaluated as $R_p = \{trp_1, trp_2, \ldots, trp_K\}$, trp_k represents k^{th} time of R-peak value, and R_p represent R-peak value. The RR value is calculated as $RR_j = trp_{j+1} - trp_j$, $j = 1,2,3, \ldots, K-1$, the complete set of RR values is defined as $RR = \{RR_1, RR_2, RR_3, \ldots, RR_{K-1}\}$.

Step 3: Feature Engineering: construct sequence of HRV values from RR signals to observe nervous system functionality. $S_{HRV} = RR \rightarrow \mathbb{R}^k$, identified feature vectors are $fv = \{fv_1, fv_2, fv_3, \ldots, fv_k\}$, and k represent count of HRV features.

Step 4: Normalization: variations in features are scaled using normalization (z − score) approach f□ = [j-μj , μ represents mean value of jth feature and aj represents standard deviation value of jth feature, normalized list of HRV vectors are f-v = Df-v1, f-v2, f-v3, … . , f-vkE .

Step 5: Generation of input Tensor: $\tilde{fv}$ is rearranged into 1D tensor that are appropriate for CNN approach, $Y \in \mathbb{R}^{1Xk}$ and the model is can be able to learn dependencies in HRV $\tilde{fv}$.

Step 6: Convolution FL: the tensor values are applied to convolution filtering process, $h_j = cp(Y * W_j + b_j)$, ′ ∗ ′ represents convolution function, W_j represents j^{th} filter, b_j represents j^{th} bias value, cp( ) represents ReLU activation function.

Step 7: Apply Pooling to reduce dimensions $P_j = \max(h_j)$.

Step 8: Aggregate features (High level): the pooled values are mapped into 1D feature vector $z = \text{Flattened}(p_1, p_2, p_3, \ldots, p_l)$, 'z' represents high value of stress.

Step 9: Multiple classification: 'z' aggregated values are applied to layers of CNN, $o = z * W_k + b_k$, probability of class is determined with help of SoftMax,

Step 10: Optimization: optimized entropy loss for Optimizing model, $L = \sum C \log(x = c|z)$ and select minimum 'L' value, {}∗ = arg min L, and '{}' represent all learning features.

Step 11: Prediction of Stress level: measured final stress value as x□ = arg max P(x = c|z), x□ = 0 represents no stress class, x□ = 1 represents moderate stress, and x□ = 2 represents heavy stress.

4. PERFORMANCE EVALUATION

Accuracy of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM (Long Short-Term Memory Network), GRU (Gated Recurrent Unit), ANN (Artificial Neural Network), RF (Random Forest), SVM (Support Vector Machine), DT (Decision Tree), KNN (Nearest Neighbors), and NB (Naive Bayes). HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 96.82 percent of accuracy due to optimization of functions and as well as supporting convolutional FL approach, from the outcome we observed that IDLMCSI shows greater accuracy than other conventional techniques and results are visualized in Figure 2.

Recall of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 96.11 percent of recall due to optimization of functions and as well as supporting convolutional FL approach, from the outcome we observed that IDLMCSI shows greater recall than other conventional techniques and results are visualized in Figure 3.

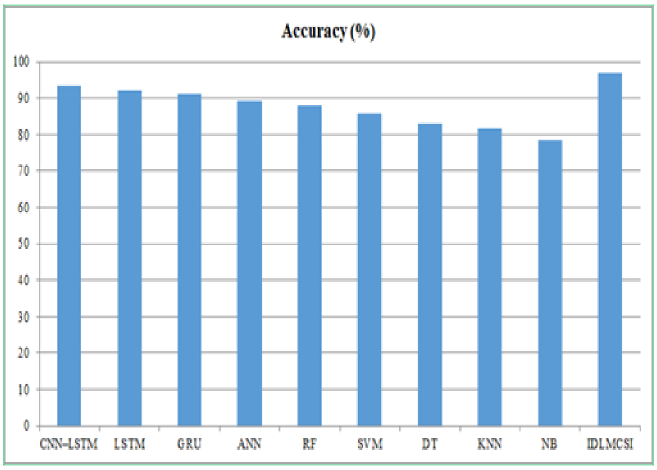

FIGURE 2. Accuracy of Various approaches

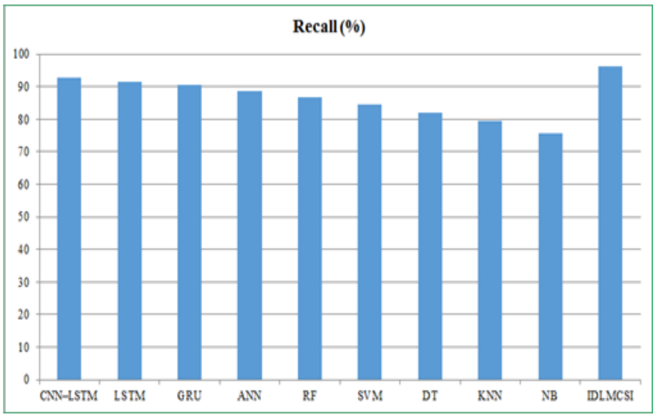

FIGURE 3. Recall of various Approaches

Precision of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 96.55 percent of precision due to optimization of functions and as well as supporting convolutional FL approach, IDLMCSI represent small FNR value and small FPR value over different types of classes, from the outcome we observed that IDLMCSI shows greater precision than other conventional techniques and results are visualized in Figure 4.

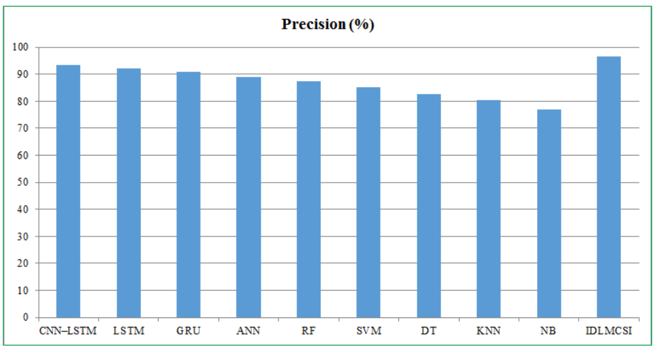

FIGURE 4. Precision of various Approaches

F1-score of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 96.34 percent of F1-score due to optimization of functions and as well as supporting convolutional FL approach, IDLMCSI represent small FNR value and small FPR value over different types of classes, from the outcome we observed that IDLMCSI shows greater F1-score than other conventional techniques and results are visualized in Figure 5.

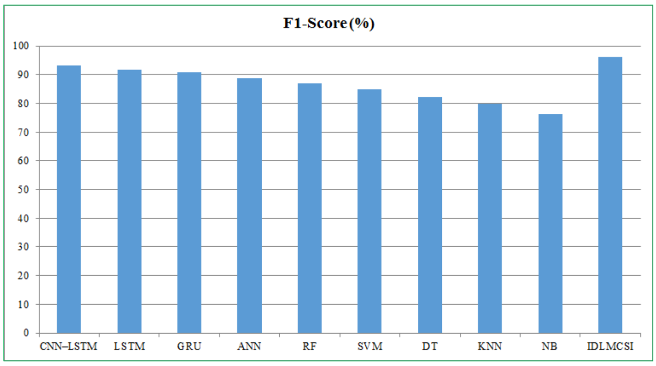

FIGURE 5. F1-score of various Approches

MCC (Matthews Correlation Coefficient) of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 0.931 value of MCC due to optimization of functions and as well as supporting convolutional FL approach, proposed model is capable to handle data samples with imbalance and also capable to handle different kinds of stress classes, from the outcome we observed that IDLMCSI shows greater MCC than other conventional techniques and results are visualized in Figure 6.

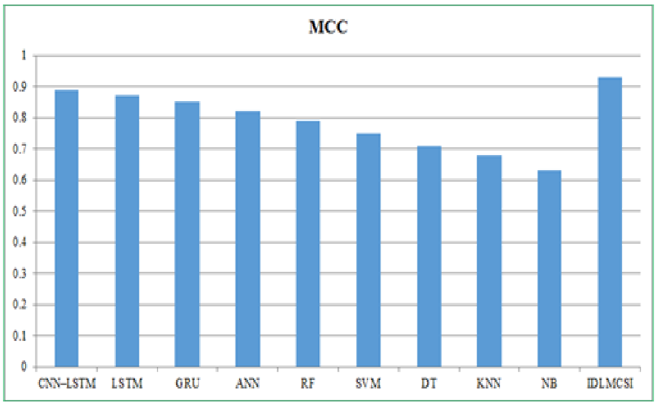

FIGURE 6. MCC values of various Approaches

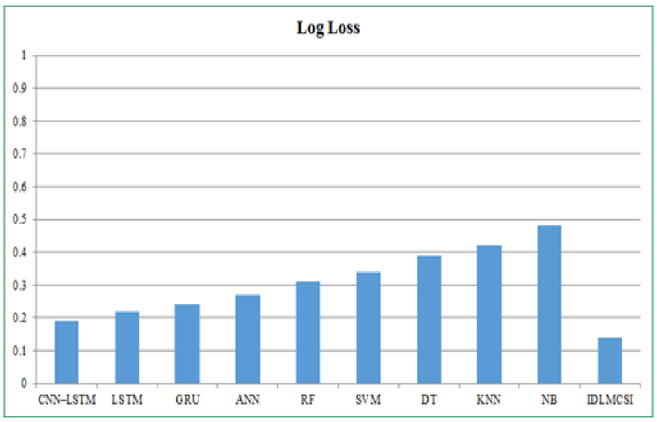

FIGURE 7. Log loss value of various Approaches

Log loss of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 0.142 value of log loss due to optimization of functions and as well as supporting convolutional FL approach, low loss rate represents more accurately predict classes with high confidence value, from the outcome we observed that IDLMCSI shows low log loss than other conventional techniques and results are visualized in Figure 7.

Cohen's Kappa of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 0.922 value of Cohen's Kappa due to optimization of functions and as well as supporting convolutional FL approach, proposed model is capable to handle data samples with imbalance and also capable to handle different kinds of stress classes, from the outcome we observed that IDLMCSI shows greater Cohen's Kappa than other conventional techniques and results are visualized in Figure 8.

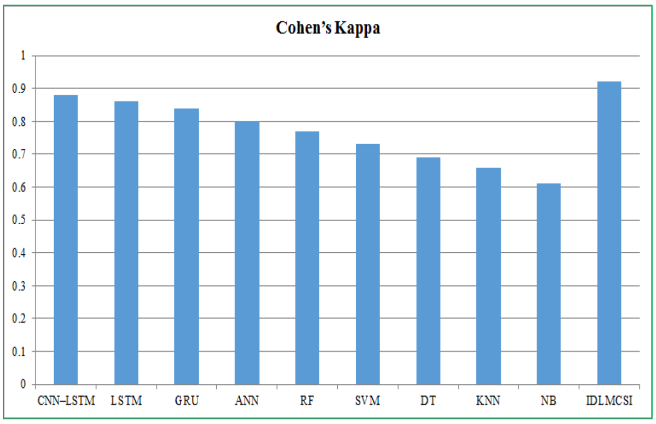

FIGURE 8. Cohen's Kappa values of various Approaches

5. CONCLUSION

Stress management of a humans are more important task, stress is a one of the crucial physiological and psychological features that shows more impact on health conditions of person and also shows impacts on various factors in his life style. Most of the conventional stress evaluation and management approaches are depends on individual matters, mostly working with static data but fail to monitor continuous data samples and deviated the predictions, mostly these approaches focused on binary classification and not supporting multiple classification. In this research we Implementation of Intelligent Deep Learning Approach for Multiple Class Stress Identification by using Observed Variable Heart Signals (IDLMCSI) approach, Variability in heart rate is gathered in the form of HRV signals through IoT wearable devices, dynamic data samples are processed using feature engineering approaches and then apply 1D CNN to learn features that belonging to stress, identified various kinds of stress movements and classified into various types classes.

Performance of proposed IDLMCSI model is evaluated and then compared with Hybrid CNN–LSTM, LSTM, GRU, ANN, RF, SVM, DT, KNN, and NB. HRV signal patterns are not captured by conventional ML approaches, proposed IDLMCSI exhibits 96.82 percent of accuracy, exhibits 96.11 percent of recall, exhibits 96.34 percent of F1-score, and exhibits 96.55 percent of precision due to optimization of functions and as well as supporting convolutional FL approach, proposed IDLMCSI exhibits 0.142 value of log loss and low loss rate represents more accurately predict classes with high confidence value, exhibits 0.922 value of Cohen's Kappa and exhibits 0.931 value of MCC due to optimization of functions and as well as supporting convolutional FL approach.

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