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METHODOLOGIES AND APPLICATION

EEG signal classification using LSTM and improved neural network algorithms

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Abstract

Neural network (NN) finds role in variety of applications due to combined effect of feature extraction and classification availability in deep learning algorithms. In this paper, we have chosen SVM, logistic regression machine learning algorithms and NN for EEG signal classification. Two-layer LSTM and four-layer improved NN deep learning algorithms are proposed to improve the performance in EEG classification. Novelty lies in one-dimensional gradient descent activation functions with radial basis operations used in the initial layers of improved NN which help in achieving better performance. Statistical features namely mean, standard deviation, kurtosis and skewness are extracted for input EEG collected from Bonn database and then applied for various classification techniques. Accuracy, precision, recall and F1 score are the performance metrics used for analyzing the algorithms. Improved NN and LSTM give better performance compared to all other architectures. The simulations are carried out with variety of activation functions, optimizers and loss models to analyze the performance using Python in keras.

Keywords LSTM · Neural network (NN) · Improved NN · Logistic regression · EEG · Accuracy

1 Introduction

Brain dynamics analysis in EEG is used to analyze drowsy driving, fatigue driving etc. Low resolutions restrict the recognition tasks in EEG. Recurrent neural network with self-adapting (RSENN) capability is applied on EEG to overcome low resolution and efficacy (Liu et al. 2016). This shows increased adaptability in virtual environment, simulated car driving using RSENN compared to other non-recurrent and recurrent NN. Data centralization is a hindrance in terms of power consumption. Eye blink artifact removal is carried out in wireless body area (WBAN) and sensor network (WESN) using modular approach, DSP (Bertrand 2015). This helps for high-density EEG, avoids data centralization and gives power efficient method. Accurate detection for intracerebral EEG with unsupervised techniques is not available. iEEG is analyzed in clinically controlled conditions for fast, objective artifact detection using CNN (Nejedly et al. 2018). The performance of CNN is checked in terms of F1 scores compared to other conventional methods of artifact detection.

Stimulating training course is carried out in EEG alpha rhythm in various networks (Kozlova et al. 2017). Functional connectivity analyzed between default mode, executive network, anterior salience and precuneus network played major role in biofeedback phenomena. Study of alpha and beta bands in EEG using neuro-imaging techniques is used to weaken irrelevant links like visuospatial network (VSN), cerebellum, etc., and forming stable interaction between anterior salience networks (ASN), primary visual network (PVN), etc. (Shtark et al. 2018). Biofeedback using fMRI gives accurate targeting in neuro-therapy. EEG is split into five bands using wavelet transforms; PCA

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is applied to reduce the size of feature vectors. ANN is used to classify it as epilepsy or healthy (Sezer et al. 2010). ROC analysis is done to evaluate the performance. Empirical mode decomposition (EMD) is used to split an EEG into IMFs; further, the phase and Euclidean distances are used to extract features. Non-stationary nature of EEG and automatic detection of focal EEG are a few present challenges. The neural networks (NN) are used for classification as focal and non-focal EEG (Zeng et al. 2019). Based on this, further medical treatment can be decided. This acts as an intelligent system and gives higher accuracy and performance.

Motor imagery (MI) tasks like leg, left hand, right hand movements in EEG are applied for brain computer interface (BCI) applications. Applying conventional power-SVM, AR-SVM and CSP-SVM on it does not give better performance. Applying deep CNN on motor imagery for feature extraction and classifications gives better classification accuracy than conventional methods (Tang et al. 2017). Novel neural network is implemented for classifying motor imagery in EEG. It involves radial function for local approximation and interpreting time sequence (Shepelev et al. 2018). Recognition accuracy and pattern classification of EEG analysis are increased by this method. Performance of proposed method is analyzed in terms of accuracy, speed and compared with SVM, MLP-NN, etc. Motor imagery analysis recognition is carried out by (Liu 2019). Fast weight reduction in filter coefficient leads to filtering problem which is overcome by using PSO and thereby effects in data processing and low SNR, high data dimension, unclean filtering problems are addressed. BPNN is used in the process. Amount of data used for analysis has greater impact on the quality of classifiers. Data augmentation and deep learning approaches are used for classifying motor imagery. CNN and Morlet wavelets applied on EEG for creating EEG frames are artificial Zhang et al. 2018b). Empirical mode is used for intrinsic mode functions and to improve accuracy, evoked potential analysis.

A novel method to improve performance in the classification techniques using radial basis function with one-dimensional gradient descent in activation functions of neural network architectures is identified. Further, the paper is organized as follows: Sect. 2 deals with all the related work carried out by various researchers, Sect. 3 explains the conventional machine learning classification algorithms, Sect. 4 discusses the two-layer LSTM and improved NN architectures. Section 5 shows the various simulations carried out to check the performances; Sect. 6 concludes the work.

2 Related work

EEG feature extraction is further helpful in clustering, classification and pattern recognition and event detection. Hand-designed EEG feature extraction methods lead to poor analytical performance. Hence, recurrent autoencoders are applied on EEG for feature extraction (Sun et al. 2018). Also, echo-state network for feature extraction (FE-ESN) gives better classification and clustering. Motor imagery classification is done based on spatial distribution of β and μ rhythms. Gradient descent and recursive classification methods give less accuracy and speed. Hence, EEG classification is done using multilayer perceptron neural network (MLP-NN) and PSO gravitational search algorithm (PSO-GSA) (Afrakhteh et al. 2018). Accuracy and speed of convergence are evaluated and compared with performance of meta-heuristic algorithms.

Neuro-cognitive performance represents the mental/cognitive capacity of human and is used for neurological studies. Sleep scoring is a neuro-cognitive effect. Sleep scoring, non-rapid eye movement and stage N1 in sleep which mean a transition between drowsiness and wakefulness is taken in (Michielli et al. 2019) recurrent neural network with long short-term memory (LSTM) blocks applied to improve classification accuracy. Deep learning is used for temporal dependencies identification in EEG. LSTM is used in (Hussein et al. 2018) to capture high-level patterns in EEG. In LSTM, fully connected layer is used for extracting robust and epileptic relevant features and softmax layer to extract predicted labels in output, and this method also maintains high level of detection performance particularly in detecting artifacts like eye movements, muscle movements and back ground noises, etc., in captured EEG. Sleep state scoring, transition between sleep stages in EEG and its time invariant features extraction are some of the major challenges. In (Supratak et al. 2017), the authors used CNN and LSTM bidirectional methods for transfer learning the features to obtain high accuracy and F1 scores for datasets with different properties and compared with statistical methods, their results and various neural network techniques (Table 1).

2.1 Mild cognitive tasks

Noninvasive scalp recordings and feature extraction for Alzheimer disease (AD), mild cognitive impairment (MCI) and health control are a tedious process. A new approach of converting EEG PSD into 2D grayscale images and then feature extraction, binary and three-way classification on those features is carried out for better classification accuracy (Ieracitano et al. 2018). Hand grasping has become a challenging task in recent neuro-study. Spatio-temporal

Table 1 Various neural network techniques from the survey

Type of ML/DL algorithm	Reference paper
Generalized regression neural network (GRNN)	Sudalaimani et al. (2018), Bevi et al. (2018)
SVM	Hamada et al. (2018), Sacca et al. (2018), Wang et al. (2016), Koda et al. (2018), Sundar and Punniyamoorthy (2019), Chunhui et al. (2018), Long et al. (2018), Asim et al. (2017), Zhou et al. (2016)
Linear regression	Kadota et al. (2018), Wu et al. (2019), Zhang et al. (2017), Rajesh et al. (2018), Khairunnahara et al. (2019), Ertas (2018)
ANN	Sezer et al. (2010), Shepelev et al. (2018), Kumar et al. (2012), Júarez-Guerra et al. (2019), Arunkumar et al. (2018), Vimala and Priya (2019)
CNN	Sors et al. (2017), Nejedly et al. (2018), Li et al. (2019), Zhang et al. (2018a), Antoniades et al. (2017), Bajaj et al. (2018), Supratak et al. (2017), Wang et al. (2018), Wei et al. (2018), Asharindavida et al. (2018)
Deep CNN	Acharya et al. (2017, 2018), Hussein et al. (2018), Jiao et al. (2017), Sturm et al. (2016), Hajinoroozi et al. (2016), Ieracitano et al. (2018), Tang et al. (2017), Wang et al. (2017), Zhao et al. (2018), Öztürk and Akdemir (2019), Wan et al. (2019)
Fuzzy neural network	Ranjan et al. (2018), Liu et al. (2016)
LSTM RNN	Michielli et al. (2019)
ERNN	Khosrowabadi et al. (2014), Liu (2019)
Neural correlations, cognition	Iturrate et al. (2018), Pang and Robinson (2018), Gomez-Pilar et al. (2018), Kinney-Lang et al. (2018), Afrakhteh et al. (2018), Bertrand et al. (2015)
Recurrent autoencoders	Sun et al. (2018)
RBF NN	Satapathy et al. (2016)
EMD, PSR, alpha feedbacks	Zeng et al. (2019), Shtark et al. (2018)
Spiking neural network	Doborjeh et al. (2015, 2017)

analysis reveals the functional connectivity and correlation between power grasps and precision grips (Iturrate et al. 2018). The presence of recurrent feedback in fronto-parietal area is proved. Low- and high-frequency components in cortical activity are not directly affecting the alpha and bold power but leads to anticorrelation. This may be due to corticothalamic and intrathalamic feedbacks present (Pang and Robinson 2018). The authors used neural network model to find out that the anticorrelation due to cortical activity may also lead to high-frequency components. Spectral filtering and feedforward NN were used for emotion discrimination from EEG. Audio visual stimuli and arousal, visual levels are investigated for emotion discrimination (Khosrowabadi et al. 2014). Coherence estimation between inputs is carried out using radial basis function, nonlinear mapping filtering (Table 2).

Schizophrenia and psychiatric disorders are analyzed in (Gomez-Pilar et al. 2018). Pre-stimulus and its theta activity destine brain dynamics of healthy person, and patients' phase coupling measures are used for minimizing prediction error. However, the inability of the patient to change the brain network while cognition is identified and hence, the predictive substrates in neuron are exposed. Mid depression recognition using EEG is done in CAD system and with CNN. Spatial, temporal and spectral features in EEG are analyzed (Li et al. 2019). Spectral features play major role, and temporal features significantly improve accuracy thereby to give objective, rapid and accurate diagnosis. Cognitive tasks are analyzed using spiking neural network (SNN). Effects of MMT (methadone maintenance treatment) and opiate dependence in EEG are the challenges; accuracy is evaluated using NeuCube model and compared with statistical, artificial intelligence methods (Doborjeh et al. 2015). Attentional bias and its effects generate spatio-temporal patterns in the brain. Spiking neural networks (SNN) finds way to analyze non-target stimuli and its attention (Doborjeh et al. 2017). It classifies better and gives better understanding and interpretation of brain functions.

Hence, cognitive tasks are related to brain condition or status at different points of the human behaviors. Sleep stage classifications, emotion detections, etc., are various scope of research in cognitive conditions in human brain.

2.2 ANN approaches

Convolutional neural network (CNN) and deep learning algorithms are applied on neurological disorders to the level or degree of depression in patients (Acharya et al. 2018). Right hemisphere and left hemisphere are analyzed,

Table 2 Various effects or phenomena in EEG

Article/paper	Year	Algorithm/NN	Technique/scheme used	Performance measures
Doborjeh et al.	(2017)	Spiking NN	Temporal and spatial patterns in attention bias conditions	Accuracy
Doborjeh et al.	(2015)	Spiking NN	NeuCube an SNN architecture to extract spatio-temporal features	Accuracy, spikes in the EEG clusters
Liu	(2019)	BP NN	Weight splitting method for BP NN, nonlinear mapping-filtering	Accuracy
Iturrate et al.	(2018)	Neural correlations	Recurrent feedback loops in fronto-parietal	Precision grips, grasping types
Bertrand et al.	(2015)	Distributed eye blink artifact	Data centralization and distributed eye blink artifact algorithms for EEG	Power consumption in near end, far end centralized EEG
Pang and Robinson	(2018)	Neural mechanisms	Intrathalamic and corticothalamic feedback-variations in strength	Alpha power, BOLD signal
Kozlova et al.	(2017)	Interactions in NN	Alpha training to increase functional connectivity	Network dynamics
Afrakhteh et al.	(2018)	Hybrid population NN	PSO with GSA for multilayer perceptron NN	Classification accuracy, speed of convergence
Gomez-Pilar et al.	(2018)	Cognitive tasks	Phase-based coupling measures	Mean, SD, cognitive variables
Kinney-Lang et al.	(2019)	Cognitive impairment	Rank correlation analysis on cognitive scores, network property	Phase-dependent connectivity, sensitivity, specificity
Sun et al.	(2018)	Recurrent autoencoders	Feature extraction using echo-state network	Accuracy
Zeng et al.	(2019)	EMD, PSR, alpha feedbacks	EEG splits to IMFs using EMD, 3D PSR for feature extraction	Accuracy
Shtark et al.	(2018)	Alpha and beta biofeedback	Stable signal acquisition using visuospatial, right executive network	Success training rate

and hyperactiveness of right hemisphere is the deteriorating factor; it is analyzed, and depression severity index (DSI) is derived. Sleep stage prediction is done using CNN (Sors et al. 2017). Sleep heart health database is used to collect EEG; class-wise patterns are learned the network. It is a supervised learning using 14-layer CNN on 30 s EEG data. Diagnosing the nonlinear and transient behavior of EEG is always a challenging task. The authors (Ranjan et al. 2018) used fuzzy c means to detect the presence and effect of K complex in EEG, backpropagation for training the network and have given a fuzzy-based neural network solution for classifying sleep stages in EEG for neurological disorders. A novel method for seizure prediction (Sudalaimani et al. 2018) with regression neural network (RNN) in a generalized manner is used to segregate normal and abnormal from EEG input. Unusual exoneration of nerve cells in brain is a disadvantage. Hence, a forecast system to identify superior elliptic seizure and performance of classifier is better at 60 Hz high pass filter applied on EEG sub-band. Convolution neural network (CNN), channel-wise known as CCNN, with restricted Boltzmann machine instead of convolutional filter known as CNN-R, is applied on raw EEG to predict cognitive states. Both show better performance in accuracy and independent component analysis (ICA) decomposition than conventional CNN, DNN (deep neural network) and other non-DL (deep learning), ANN and RNN algorithms (Table 3).

Visual perception of EEG for epileptic abnormalities is a time-consuming process, limited in artifact avoidance, depends on reader expertise level. Hence, CAD (computer-aided diagnosis) method using machine learning techniques and deep neural network is used in (Acharya et al. 2017) to differentiate preictal, normal and seizure classes in EEG. Mental load and cognitive tasks complexity are challenges to be addressed in EEG. Machine learning algorithms are used for classifying mental load in (Jiao et al. 2017). Deep learning and CNN are used to extract temporal, spectral and spatial features from EEG. A novel fusion strategy is modeled by the authors. Deep neural network (DNN) does not reveal the underlying decision phenomena in complex perception. In (Sturm et al. 2016), the authors introduced a layerwise relevance perception (LRP) in DNN which give heat maps pin pointing EEG patterns at each point in single trails; complex classification tasks are addressed. By this method, classification accuracy of DNN is improved with the help of LRP. Mental workload assessment under various conditions for EEG is a challenge. 3D and deep neural CNN (DN3DCNN) are

Table 3 Methods in artificial neural network for EEG

Article/paper	Year	Algorithm/NN	Technique/method used	Performance measures
Sudalaimani et al.	(2018)	RNN	Seizure prediction method—10 sub-bands	Sensitivity, specificity
Sezer et al.	(2010)	ANN	PCA to reduce size of extracted features, five different ANNs	ROC analysis, accuracy, specificity, sensitivity
Kumar et al.	(2012)	ANN	DWT and approximate entropy, FF BPN, LM optimization	Accuracy, specificity, sensitivity
Arunkumar et al.	(2018)	ANN	Three fiction computer vision strategies for enhancing, segmenting and filtering images	Texture, HOG features, accuracy, precision, sensitivity
Júarez-Guerra et al.	(2019)	ANN	Maximum overlap DWT, one to one binary tree	Accuracy
Shepelev et al.	(2018)	NN for BCI	Radial basis function for local point approximation	Accuracy, speed of control

Table 4 Methods in convolutional neural network for EEG

Article/paper	Year	Type of NN	Technique/scheme used	Performance measures
Sors et al.	(2017)	CNN	Five class prediction of sleep stages	Kappa, accuracy, F1 micro, F1 macro
Ieracitano et al.	(2018)	CNN	CNN with Relu and pooling layer	Accuracy in 2-way and 3-way classification
Nejedly et al.	(2018)	CNN	ML approach for artifact removal in intracerebral EEG	F1 scores, precision, recall
Li et al.	(2019)	CNN	Transfer learning applied on ConvNet architecture	Accurate diagnosis of mild depression
Antoniades et al.	(2017)	CNN	Convolved filters used for interictal epileptic discharge-IED	Accuracy, running time, TP, FP
Bajaj et al.	(2018)	CNN	Converting EEG to T-F representation using STFT	Transfer learning, accuracy
Supratak et al.	(2017)	CNN	CNN-features, bidirectional LSTM-transition rules in sleep	Accuracy, F1 scores
Wang et al.	(2018)	9-layer CNN	Stochastic pooling in CNN for micro-bleeding detection in cerebrum (CMB)	Accuracy, precision, sensitivity, specificity
Wei et al.	(2018)	Deep dense CNN	Deep dense super resolution (DDSR) technology for CT, MRI images-object recognition	High-level features
Zhang et al.	(2018a)	Recurrent 3D CNN	Morlet wavelet transforms on topoplots, RCNN to extract spectral, spatio-temporal features	Accuracy

applied on EEG features for binary classification (Zhang et al. 2018a). Morlet wavelet is used for cross-talk mental workload analysis (Table 4).

Hence, ANN acts as basic structure for most of the machine learning algorithms. For further performance improvement, deep learning approaches can be used which depends on NN (neural network) architectures.

2.3 Epileptic seizures

Slow searching in and around the solution which is optimum is a major challenge in epileptic seizure analysis. Canonical PSO and gradient descent are used to overcome this challenge (Satapathy et al. 2016); neural network with radial basis function (RBFNN) is used to optimize MSE and improve classification accuracy. Predictive properties of EEG are analyzed for early onset epilepsy detection in children from age group 0–5 years. Rank correlation analysis (Kinney-Lang et al. 2018) is performed; phase connection dependency is proved by obtaining higher sensitivity in cognitive impairment (CI) of epilepsy. Head ache, dementia, seizures, etc., are major effects during EEG analysis. Discrete wavelet transform is used to split EEG to sub-bands and then calculate approximate entropy and detailed coefficients. The values are less during seizure activity compared to normal EEG (Kumar et al. 2012).

Table 5 ML/DL techniques for epileptic seizures

Article/paper	Year	ML/DL NN	Scheme/logic used	Performance measures
Asharindavida et al.	(2018)	ML	EMD, spectral analysis, window-based analysis, regression analysis	Spectral peaks, % of seizure detection(IMF area
Acharya et al.	(2018)	DCNN	Classifier automatic separation of depression and normal EEG	Accuracy 93.5% in left hemisphere and 96% in RH
Acharya et al.	(2017)	DCNN	CAD system to identify epileptic abnormalities	Accuracy, sensitivity, specificity
Zhao et al.	(2018)	DCNN	Integrated DCNN to avoid complicated feature extractions and reduce interference	Accuracy, error rate
Hussein et al.	(2018)	DNN	Epileptic seizure detection using temporal dependencies in EEG	Accuracy, sensitivity, specificity
Jiao et al.	(2017)	DNN	Single- and double-model CNNs for classifying mental loads	Test error %
Sturm et al.	(2016)	DNN	Layerwise relevance in DNN	Accuracy, resolution
Tang et al.	(2017)	DNN	Five-layer CNN classifies MI tasks	Accuracy
Hajinoroozi et al.	(2016)	DNN	RBM replacing convolutional filter	Accuracy
Wang et al.	(2017)	DNN	CNN, LSTM on motor imagery EEG, STFT to train EEG	Accuracy, paired *t* test
Ranjan et al.	(2018)	Fuzzy NN	K complex detector for nonlinear and dynamic character	Accuracy, sensitivity, specificity
Liu et al.	(2016)	Recurrent Fuzzy (RFNN)	Gradient descent learning to increase adaptability of EEG	Root Mean Square Error
Satapathy et al.	(2016)	RBF NN	Radial basis function NN, PSO for overcoming slow searching of optimum solution	Accuracy
Michielli et al.	(2019)	LSTM RNN	Cascaded RNN for sleep scoring stages identification	Single class, two class and four class classification
Khosrowabadi et al.	(2014)	ERNN	Six-layered FFNN, shift register and radial basis function	Accuracy

Backpropagation NN with feedforward, levenberg optimization is used to classify EEG to obtain high accuracy (Table 5).

Epilepsy and its three states namely healthy, ictal and interictal are classified. FIR and IIR are used for noise reduction. Maximum overlap DWT is used for frequency decomposition. One versus one (OVO) and binary tree are used for primary classification (Júarez-Guerra et al. 2019). Weighted strategy and voting methods are used for secondary classification. By halftime training, the proposed method achieves accuracy compatible with other classifiers. Interictal epileptic discharge (IED) and time difference between them are analyzed using multichannel intracranial EEG with discrete order, and hence, the classification performance is improved (Antoniades et al. 2017). Deep learning model is made hierarchical using convolved filters in deep layers. Focal EEG epileptic area identification is done using STFT and end–end transfer learning to extract features (Bajaj et al. 2018). Features are extracted from AlexNet, VGG19, VGG16, etc. Then, it is applied to *k*-NN classifier to achieve high accuracy.

Hence, seizures, schizophrenia, Alzheimer are few diseases which can be diagnosed using classification algorithms for its accuracy of disease detection. Based on the literature survey, a novel method is derived to improve performance in the classification techniques using radial basis function with one-dimensional gradient descent in activation functions of neural network architectures. In this paper, we have used relu activation function in the initial layers and sigmoid activation function in the last layer of proposed INN. We have checked the performances with various activation functions like relu, selu, sigmoid, softmax and softplus; optimizers like Adam, sgd, Nadam, RMSprop and adagrad; loss models like binary cross-entropy, mean square error, mean squared logarithmic error, categorical hinge logcosh for LSTM and INN.

3 Conventional methods

SVM and logistic regression are supervised classification algorithms. If the number of features is higher, then the number of input channels may also lead to overfitting problem. Regularization in selecting the features for classification model will solve this problem in supervised learning.

3.1 SVM classification

The key of SVM classifier is to select proper kernel function. There exists many classical kernel methods namely perceptron, linear, RBF and polynomial. The regulation, kernel parameters (C, γ) and their optimal combination will give low general testing error (GTE). SVM deals better even in large number of elements and small training data. SVM takes output structure and spatial contiguity as features and can give higher classification accuracy. Boosting, AdaBoost and Wang's boost algorithms for SVM learn the imbalanced data better and give good results.

Performance of SVM can be improved by using changes in time complexity as $O(n^3)$. However, it neglects the classification of observation positions and position similarities. New setbacks can be introduced by deciding the distance-based weights and sign-based classifier to get improved ensemble classifier. Boosted and modified boosted algorithm for SVM help in classification of multi-criteria inventory problems. SVM acts as a base classifier for imbalance data learning and analysis. It is the classifier which uses kernel function efficiently. Modified boosted and Wang boosted are two types of SVM for further improvement in the performance of SVM.

3.2 Logistic regression classification

Repeated learning of same information through more number of input features to classification algorithm or number of features higher the number of input channels may lead to overfitting problems. Laplacian method for selecting features and with sparse logistic regression will give better performance compared to univariate analysis. Euler elastic-based multi-nominal logistic regression can be applied for multi-class classification and can work with minimum energy and overcoming overfitting problem. Total variation logistic regression (TVLR), Euler elastic logistic regression(EELR) and sparse logistic regression (SLR) are various methods that can be applied on EEG for classification. Among these three, EELR works better in terms of finding larger number of active regions and discriminative regions for brain using fMRI as input in analysis.

Multinomial logistic regression can be used to feed the input features and classify the respective class label. In multi-class logistic regression classification problem, there exists separate linear discriminate function for each class.

If $x = \{x_1, x_2, x_3, \ldots x_n\}$ are features in RF domain, y be the class label, encoding vector is given by $\{y^{(1)}, y^{(2)}, y^{(3)}, \ldots y^{(c)}\}$ where c is the number of class labels. The linear discriminate function of each class is given by

$$d(x, w^c) = \sum_{n=1}^{F} w_n^c x_n; \quad c = 1, 2, 3 \ldots C \tag{1}$$

w^c is the weight assigned to each feature and according to multi-class logistic regression, the probability that x belongs to class is given by

$$p\left(y^c = \frac{1}{x}, w^c\right) = \frac{e^{d(x,w^c)}}{\sum_{i=1}^{c} e^{d(x,w^i)}} \tag{2}$$

where w^c represents weights of all classes.

3.3 Neural network classification

Neural network can work based on different wavelets; hence, they can combine feature extraction, classification steps together and be part of deep learning techniques. Wavelet-based neural network acts as a binary classifier, and hence, combination and decision strategy to be used are based on N-class problem in different applications.

A multi-dimensional feedforward neural network is used for regression analysis with multi-variables. R represents radial function in Fig. 1. Input vectors are accepted and then applied to radial function followed by one-dimensional wavelet function. Linear combiner is used at the end to combine all the signals for classification. Computational time, adjusting the parameters and weights in the path are the challenging task in neural network architectures. Mean, standard deviation, kurtosis and skewness are the four input features used in our work. The effectiveness of neural network depends on the wavelet being used as activation function in each layer. We have used relu and sigmoid as the basic activation functions in this NN.

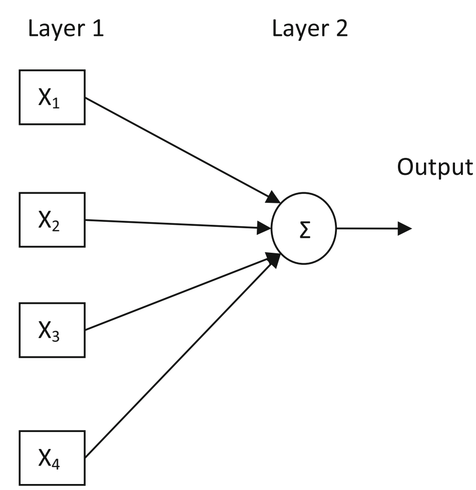


Fig. 1 Architecture of neural network (NN)

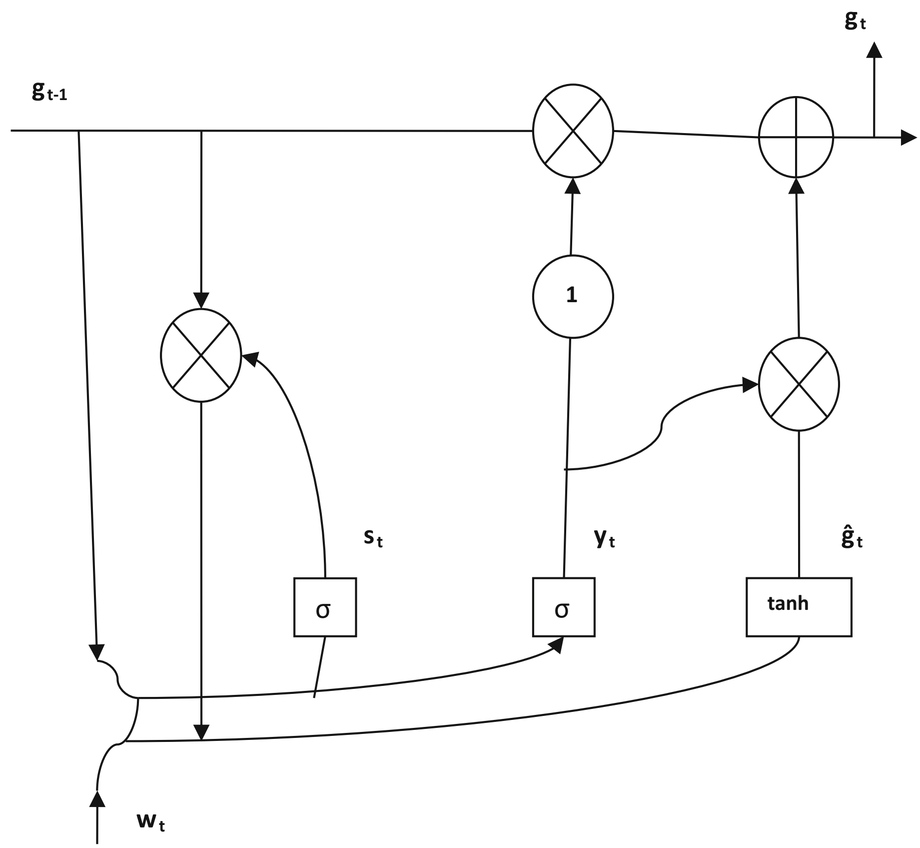


Fig. 2 Internal structure of long short-term memory (LSTM)

SVM, logistic regression and neural network (NN) and improved version of NN are machine learning approaches, whereas LSTM is deep learning approach for which the basic structure of all deep learning approaches is neural network.

In our work, we have implemented conventional methods like SVM, logistic regression and NN. Further, we have proposed improved version of neural network and appropriate LSTM structure for our EEG classification.

4 Proposed method

To improve the performance of NN architecture, a four-layer improved NN and LSTM are designed. Both are implemented using Python, and comparison analysis is carried out with statistical features. LSTM is long short-term memory approach which removes overfitting problem caused in basic RNN structure of deep learning classification algorithm. Moreover, it has been the base for many further algorithms came up in deep learning.

4.1 LSTM classification

Long short-term memory (LSTM) is based on recurrent neural network (RNN), which is a deep learning algorithm. RNN consists of recurrent structures which locally feed the firing strength thereby external registers or memories are not required for storing previous outputs. Computational complexity is low in LSTM due to recurrent structures used in RNN (Fig. 2).

LSTM works based on the below operations.

$$y_t = \sigma\left(W_y \cdot [g_{t-1}, w_t]\right) \tag{3}$$

$$s_t = \sigma(W_s \cdot [g_{t-1}, w_t]) \tag{4}$$

$$\hat{g}_t = \tanh(W \cdot [s_t * g_{t-1}, w_t]) \tag{5}$$

$$g_t = (1 - y_t) * g_{t-1} + y_t * \hat{g}_t \tag{6}$$

Structure learning and parameter learning are carried out as two phases in RNN. Membership functions are added to the nodes based on input variable. Gaussian membership function is assigned using mean and variance. Spatial firing and temporal firing are carried out to assign single-dimensional membership functions. Structure learning is all about to decide when to generate a rule and activate it with firing strength higher than the threshold (0, 1) for each input. Parameter learning is carried out after structure learning to minimize the error cost function.

4.2 Improved neural network classification

To improve the performance of neural network, an improved neural network with four layers is designed with relu, relu, relu and sigmoid activation functions in each layer, respectively. It also uses Adam optimizer and binary cross-entropy loss model. In general, there is no fixed condition on number of neurons to be selected in the hidden layer. Fully connected layer is used throughout the neural network (Fig. 3).

Weights and threshold values are calculated and used as optimization variables. Normalization of the input is carried out before applying to neural network architecture for classification. Parameters are tuned using four fully connected layers and dropouts wherever required in the architecture. Kernels are used to derive feature maps. Nonlinear activation functions like relu with radial basis operations are used to extract nonlinear features. Fully connected layer connects every neuron in one layer to every neuron in the next layer. As only convolution layers and dropouts are used in our network, performance is found better compared to LSTM considered and conventional NN. Pooling layers can be used to still increase the performance on NN.

5 Results and discussion

The proposed LSTM and improved neural network are trained and tested using Python in 2 GHz processor with 16 GB RAM. EEG data are collected from Bonn university database. Twenty channels from the EEG are used for classification using SVM, logistic regression, neural network, LSTM and improved neural network algorithms. Statistical features like mean, standard deviation, skewness and kurtosis are extracted based on the formulae as shown.

$$\text{Mean} = \frac{1}{M}\sum_{j=1}^{M} x_j \tag{7}$$

$$\text{standard deviation (SD)} = \sqrt{\frac{1}{M}\sum_{j=1}^{M}\left(x_j - \text{mean}\right)^2} \tag{8}$$

$$\text{Skewness} = \frac{\frac{1}{M}\sum_{j=1}^{M}\left(x_j - \text{mean}\right)^3}{\text{SD}^3} \tag{9}$$

$$\text{kurtosis} = \frac{\frac{1}{M}\sum_{j=1}^{M}\left(x_j - \text{mean}\right)^4}{\text{SD}} \tag{10}$$

Features extracted are recorded in Table 6. It is further applied to machine learning and deep learning classification algorithms like support vector machine (SVM), logistic regression, neural network (NN), long short-term memory (LSTM) and improved neural network algorithms for classification. Accuracy, precision, recall (sensitivity) and F1 score are the performance metrics considered to analyze the obtained results. Machine learning algorithms perform two-step analysis, and deep learning algorithms perform single-step analysis in classification. The results of SVM, logistic regression and neural network methods are compared. Also, improvement is carried out in neural network by increasing number of layers and then obtained results in neural network, LSTM and improved neural network are compared.

5.1 ML algorithms: performance comparison

Table 7 shows the results obtained in machine learning algorithms SVM and logistic regression. In addition, results

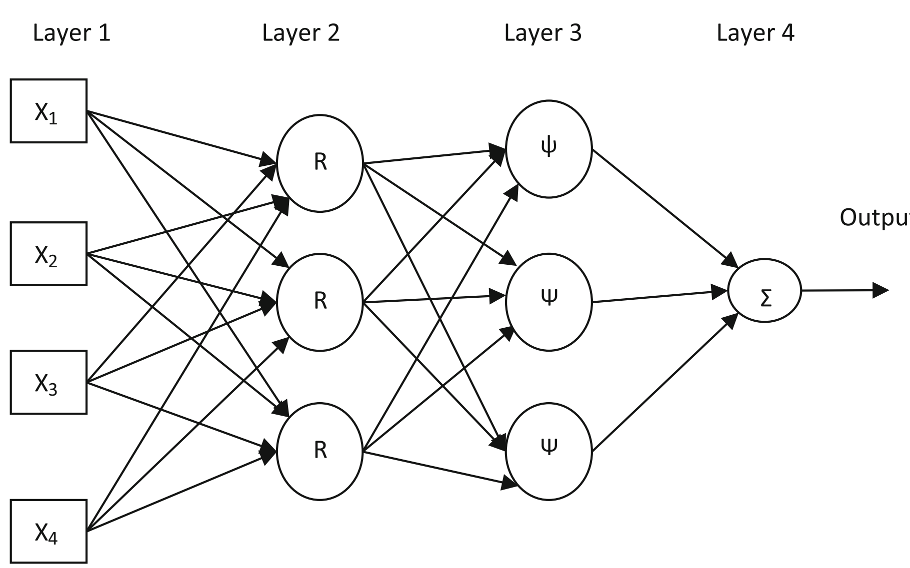


Fig. 3 Architecture of improved neural network (INN)

Table 6 Features extracted from 20 channels of EEG signal

Channel number	Mean	Standard deviation (SD)	Kurtosis	Skewness
0	4316.5937	186.3952	− 0.6868	0.4392
1	4312.7485	186.7973	− 0.6738	0.4591
2	4312.7485	186.7973	− 0.6738	0.4591
3	4312.1606	184.6089	− 0.6939	0.4432
4	4312.1606	184.6089	− 0.6939	0.4432
5	4316.5937	186.3952	− 0.6868	0.4392
6	4312.1606	184.6089	− 0.6939	0.4432
7	4312.1606	184.6089	− 0.6939	0.4432
8	4316.2270	183.6127	− 0.6968	0.4225
9	4316.1899	184.2043	− 0.7162	0.4146
10	4306.0083	183.9468	− 0.7344	0.4394
11	4307.1435	183.9930	− 0.6866	0.4359
12	4307.1435	183.9930	− 0.6866	0.4359
13	4309.2299	184.2458	− 0.7411	0.4456
14	4306.0083	183.9468	− 0.7344	0.4394
15	4312.7485	186.7973	− 0.6738	0.4591
16	4306.5561	184.0595	− 0.7739	0.4418
17	4306.0083	183.9468	− 0.7344	0.4394
18	4298.7905	185.0739	− 0.7143	0.4757
19	4307.9477	183.8284	− 0.7111	0.4562

Table 7 Accuracy, precision, recall and F1 score using SVM, logistic regression and NN classification methods

	SVM	Logistic regression	Neural network (NN)
Accuracy	0.6959	0.5300	0.6143
Precision	0.7050	0.5374	0.6272
Recall	0.7036	0.6245	0.6165
F1 score	0.7043	0.5777	0.6218

of NN are also tabulated. Table 8 shows results obtained by deep learning algorithms. Analysis of the proposed architectures is carried out with Adam optimizer, binary cross-entropy loss model and relu activation function in the initial layers, sigmoid activation function in the last layer, respectively. Figure 4 shows the comparison of all the five algorithms performance in terms of accuracy, precision, recall and F1 score. F1 score metric used in the analysis is defined as below.

$$\text{True Positive Rate} = \frac{\text{True Positive}}{\text{False Negative} + \text{True Positive}} \tag{11}$$

$$\text{Positive Predictive Value} = \frac{\text{True Positive}}{\text{False positive} + \text{True Positive}} \tag{12}$$

$$\text{F1 Score} = 2 \cdot \frac{\text{True Positive Rate} \cdot \text{Positive Predictive Value}}{\text{True Positive Rate} + \text{Positive Predictive Value}} \tag{13}$$

5.2 Proposed INN and LSTM: performance analysis

Analysis of neural network (NN), LSTM and improved NN is carried out with different activation functions, optimizers and loss models. Figures 5, 6, 7, 8, 9, 10, 11, 12 and 13 represent NN, INN and LSTM performances. Figure 5 shows performance of two-layer NN with various activation functions. Relu followed sigmoid activation functions

Table 8 Accuracy, precision, recall and F1 score using NN, LSTM and improved NN classification methods

	Neural network (NN)	LSTM	Improved neural network
Accuracy	0.6143	0.7138	0.7892
Precision	0.6272	0.7166	0.7298
Recall	0.6165	0.7338	0.9370
F1 score	0.6218	0.7251	0.8205

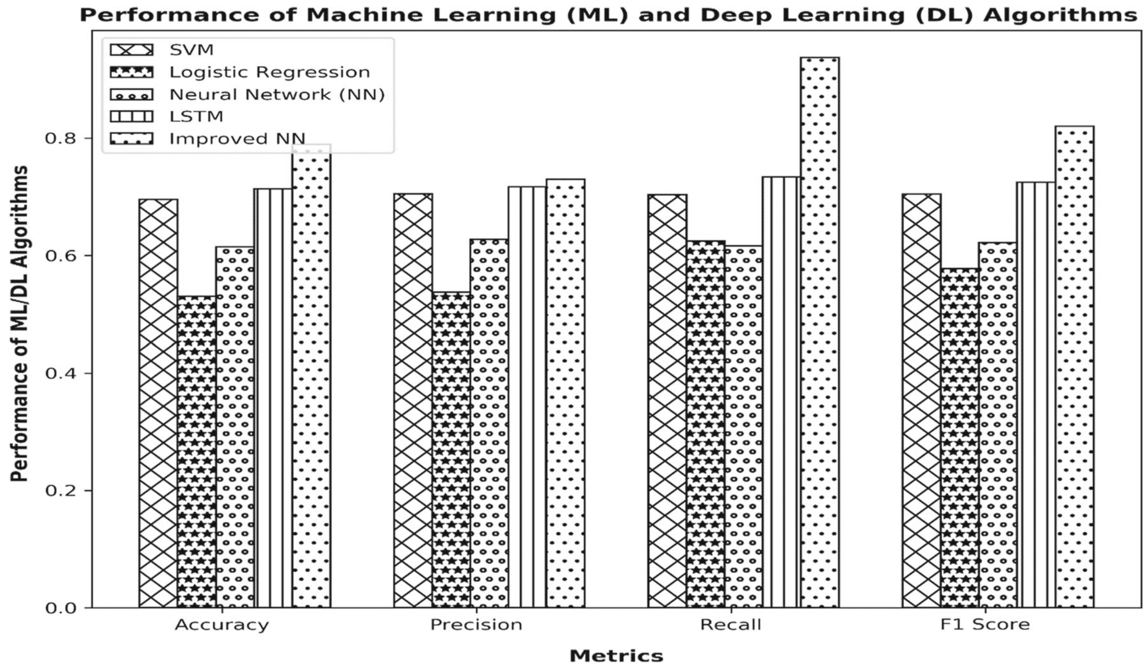
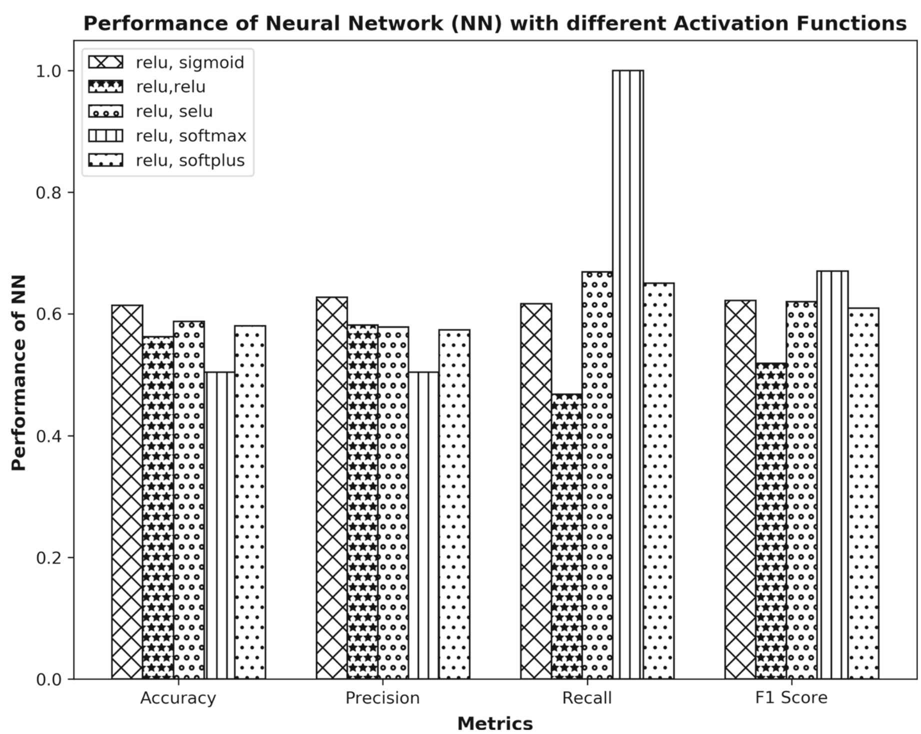


Fig. 4 Performance of ML (SVM, logistic regression) and DL (NN, LSTM and improved NN) algorithms

Fig. 5 Neural network with different activation functions



in consecutive layers and gave better accuracy, precision and F1 score compared to other combinations. However, relu followed by selu activation functions give better recall compared to other set of combinations in the two-layer NN. Figure 6 shows performance of two-layer NN with Adam, sgd, Nadam, RMSprop and adagrad optimizers. Nadam optimizer gives better performance compared to other optimizers in NN. Figure 7 shows performance of two-layer NN with binary entropy, mean square error, mean squared logarithmic error, categorical hinge and logcosh loss models. Logcosh gives better performance compared to other loss models in NN. Figure 8 shows performance of four-layer INN with various activation functions. Relu, relu, relu followed by sigmoid in consecutive layers give

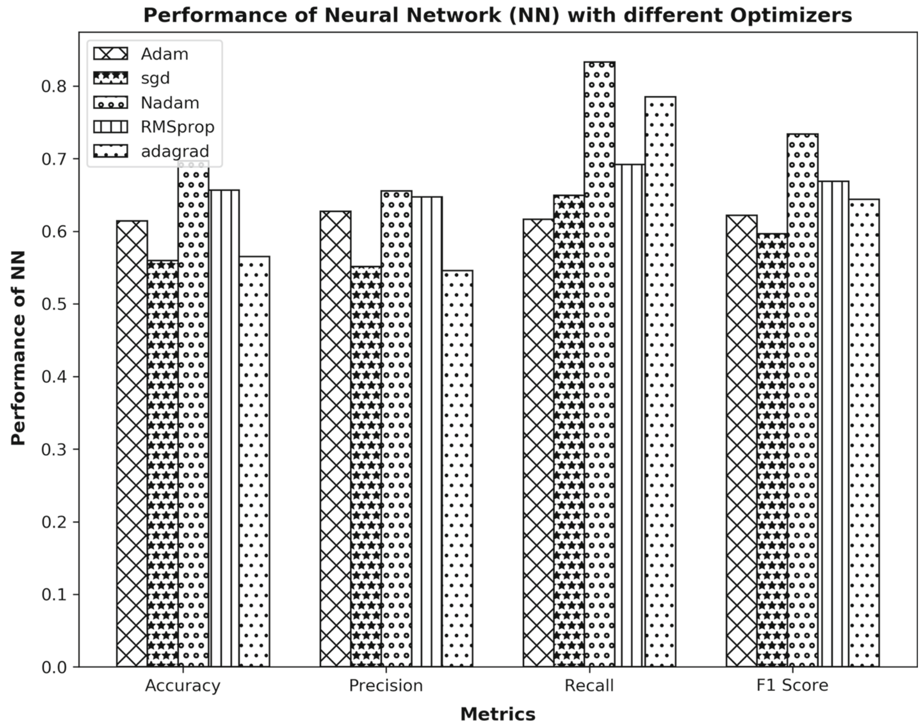


Fig. 6 Neural network with different optimizers

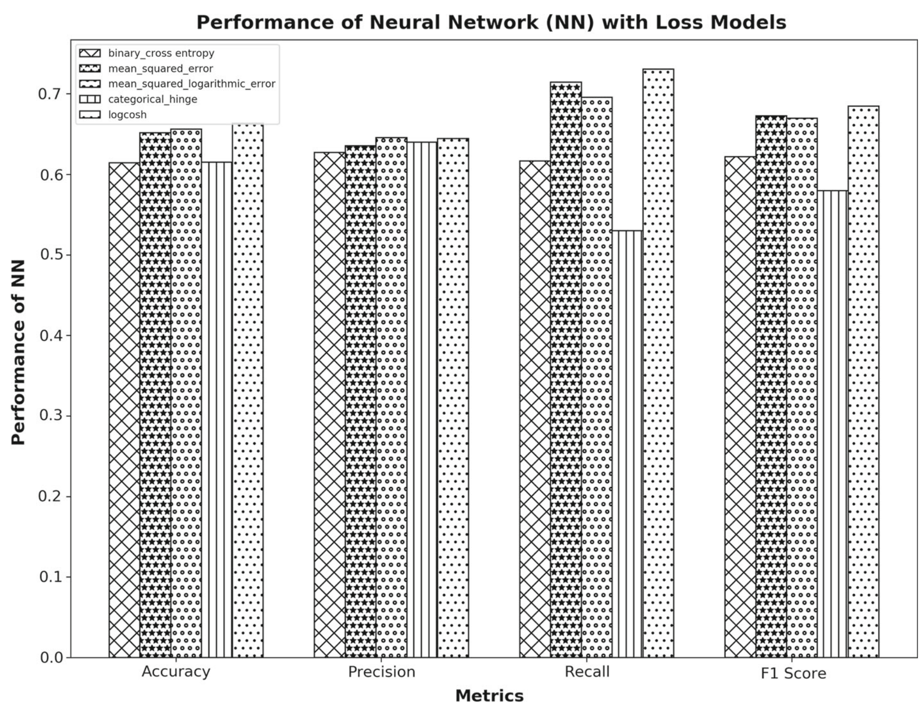


Fig. 7 Neural network with different loss models

better accuracy, precision, recall and F1 score compared to other combinations in INN. Figure 9 shows performance of four-layer INN with Adam, sgd, Nadam, RMSprop and adagrad optimizers. Adam optimizer gives better accuracy, precision and F1 score, whereas adagrad optimizer gives better recall in INN compared to other optimizers. Figure 10 shows performance of four-layer INN with binary entropy, mean square error, mean squared logarithmic error, categorical hinge and logcosh loss models. Binary cross-entropy loss model gives better results in INN compared to other loss models.

Figure 11 shows performance of two-layer LSTM with various activation functions. Sigmoid activation function gives better accuracy, recall and F1 score in LSTM

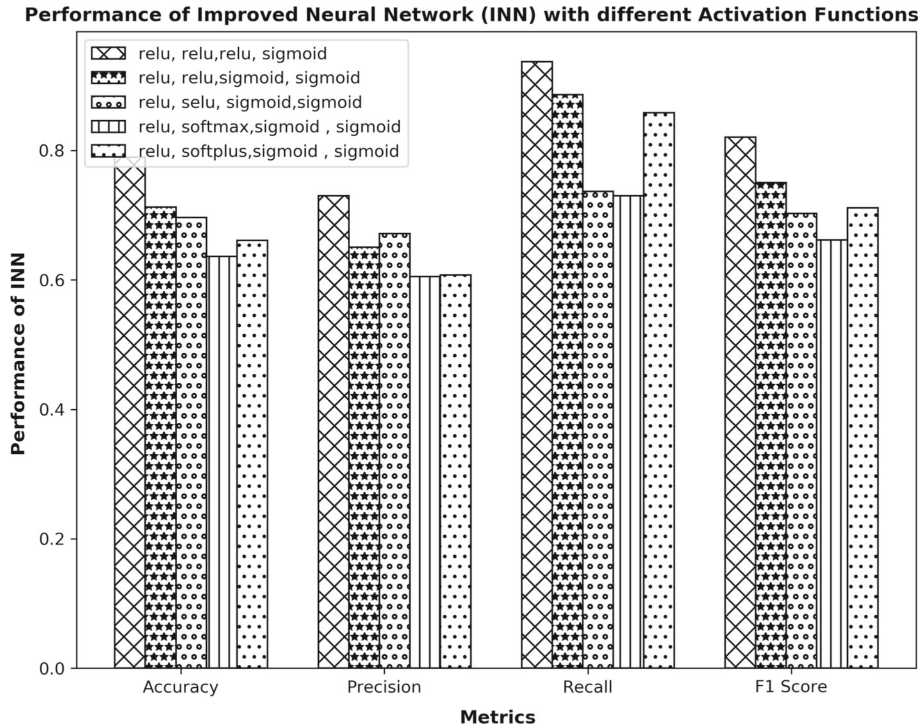


Fig. 8 Improved neural network with different activation functions

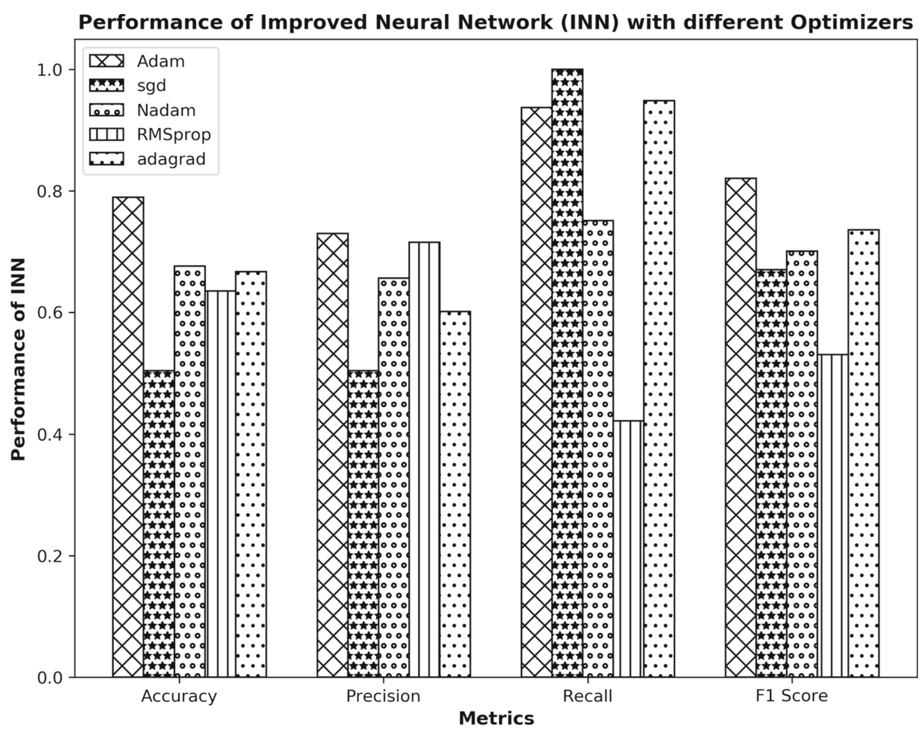


Fig. 9 Improved neural network with different optimizers

compared to other relu, selu, softmax and softplus activation functions. However, softplus activation function in LSTm gives better precision compared to others. Figure 12 shows performance of two-layer LSTM with Adam, sgd, Nadam, RMSprop and adagrad optimizers. Adam optimizer performs better compared to other optimizers used in LSTM. Figure 13 shows performance of two-layer LSTM with binary entropy, mean square error, mean squared logarithmic error, categorical hinge and logcosh loss models. Binary cross-entropy loss model gives better accuracy, recall and F1 score compared to other loss models. However, mean squared error loss model gives better precision compared to others in LSTM.

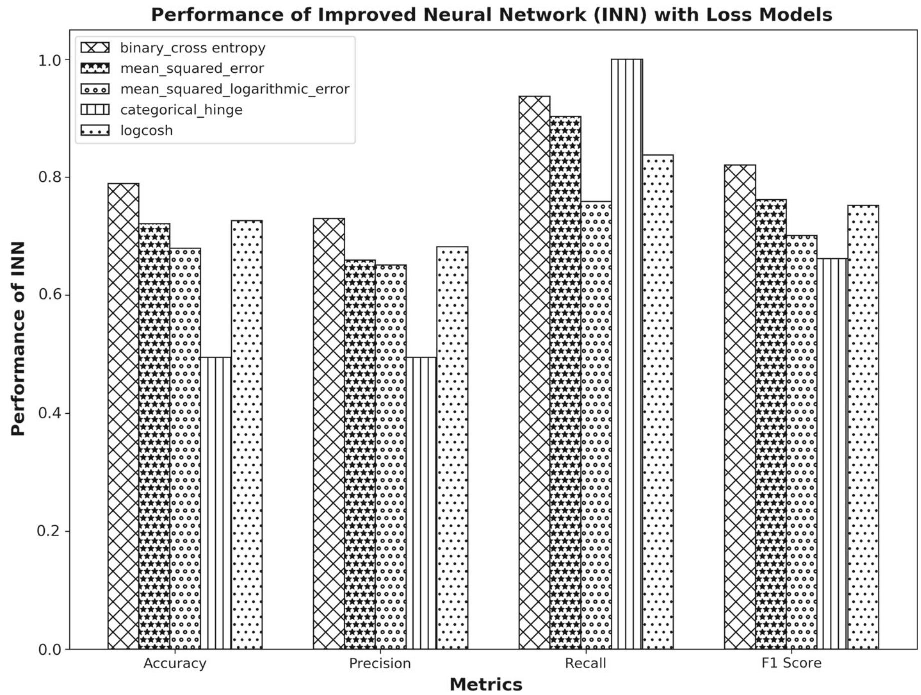


Fig. 10 Improved neural network with different loss models

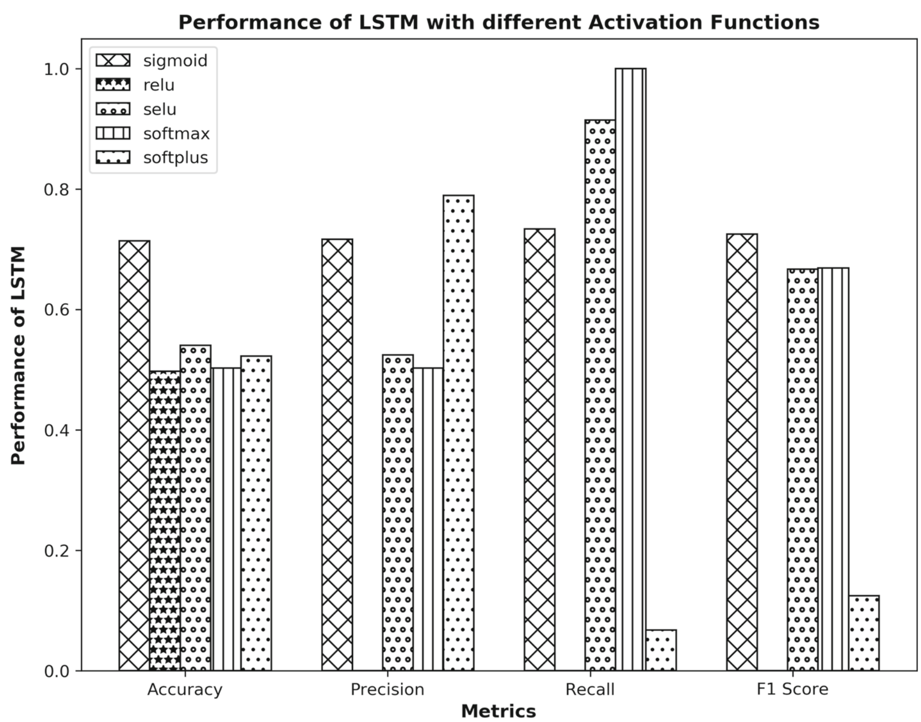


Fig. 11 LSTM with different activation functions

Figures 14, 15, 16, 17 and 18 show NN, LSTM and INN performance with various optimizers. Figure 14 shows performance of two-layer NN, two-layer LSTM and four-layer INN with Adam optimizer. Improved NN gives better accuracy, precision, recall and F1 score compared to other architectures with Adam optimizer. Figure 15 shows performance of two-layer NN, two-layer LSTM and four-layer INN with sgd optimizer. NN gives better accuracy, precision, recall compared to other architectures with sgd optimizer. However, LSTM and INN give equally better F1 score compared to NN with sgd optimizer. Figure 16 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with Nadam optimizer. NN gives better accuracy, precision, recall and F1 score compared to other

Fig. 12 LSTM with different optimizers

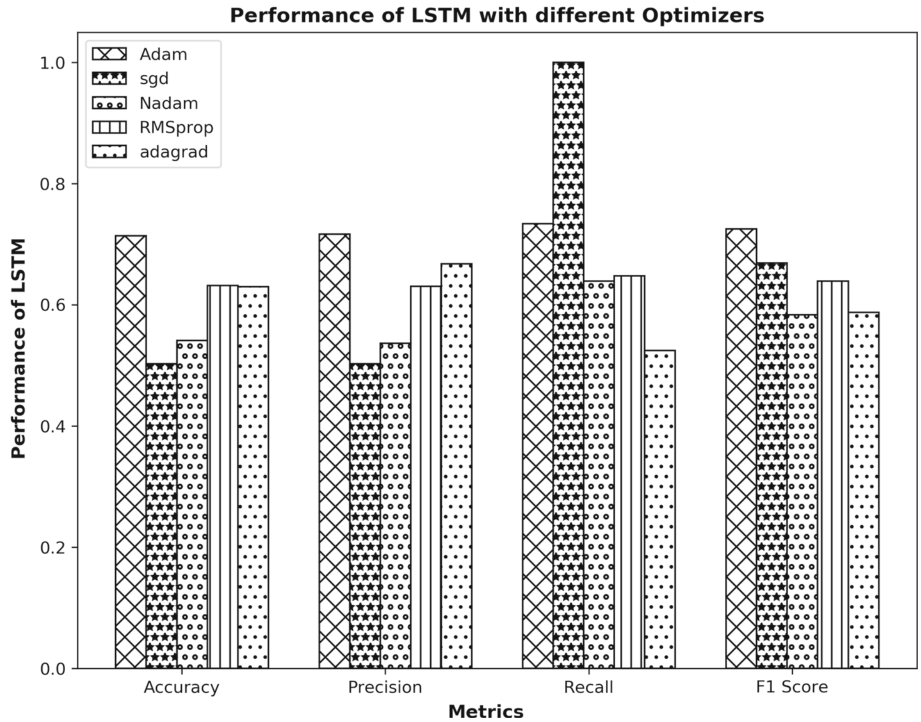
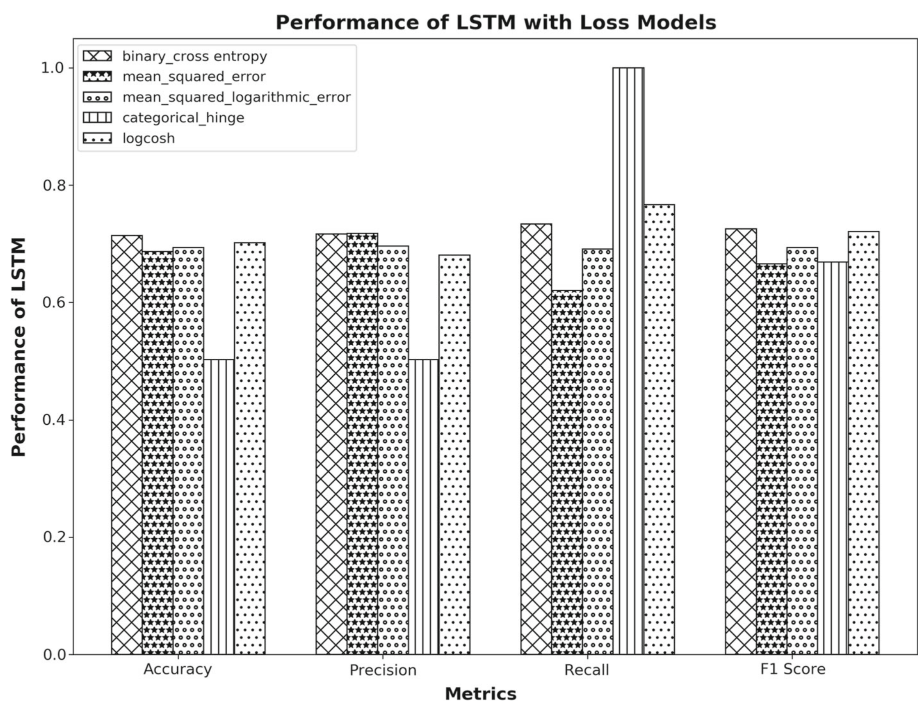


Fig. 13 LSTM with different loss models



architectures with Nadam optimizer followed by INN and then comes the performance of LSTM. Figure 17 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with RMSprop optimizer. NN gives better accuracy, recall and F1 score compared to other architectures with RMSprop optimizer. LSTM performs better than INN; however, INN gives better precision compared to NN, LSTM with RMS prop optimizer. Figure 18 shows performance of two-layer NN, two-layer LSTM and four-layer INN with adagrad optimizer.

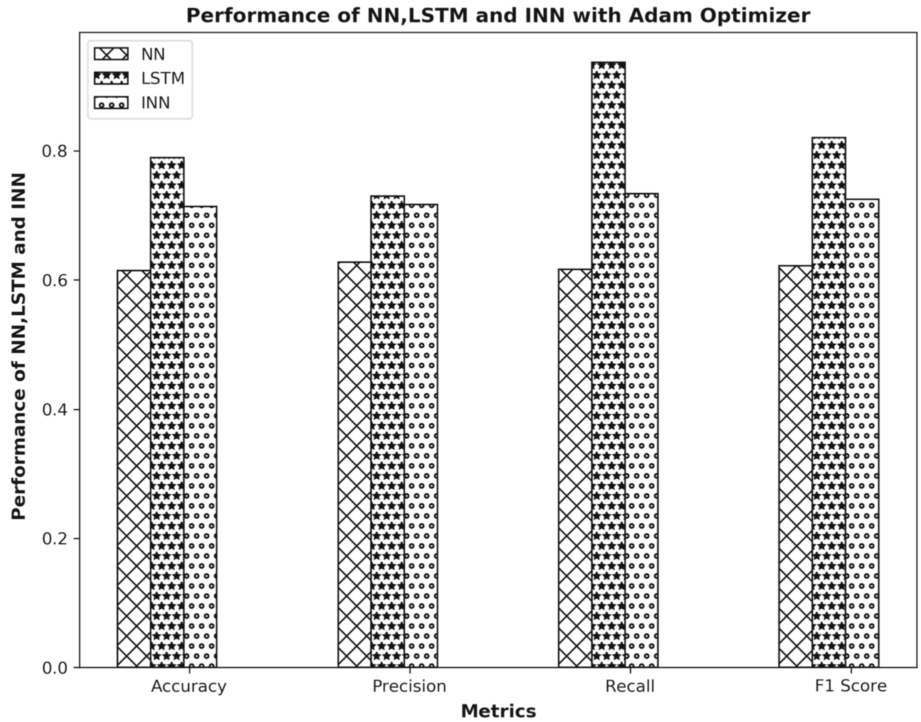


Fig. 14 Performance of neural network (NN), LSTM and improved NN with Adam optimizer

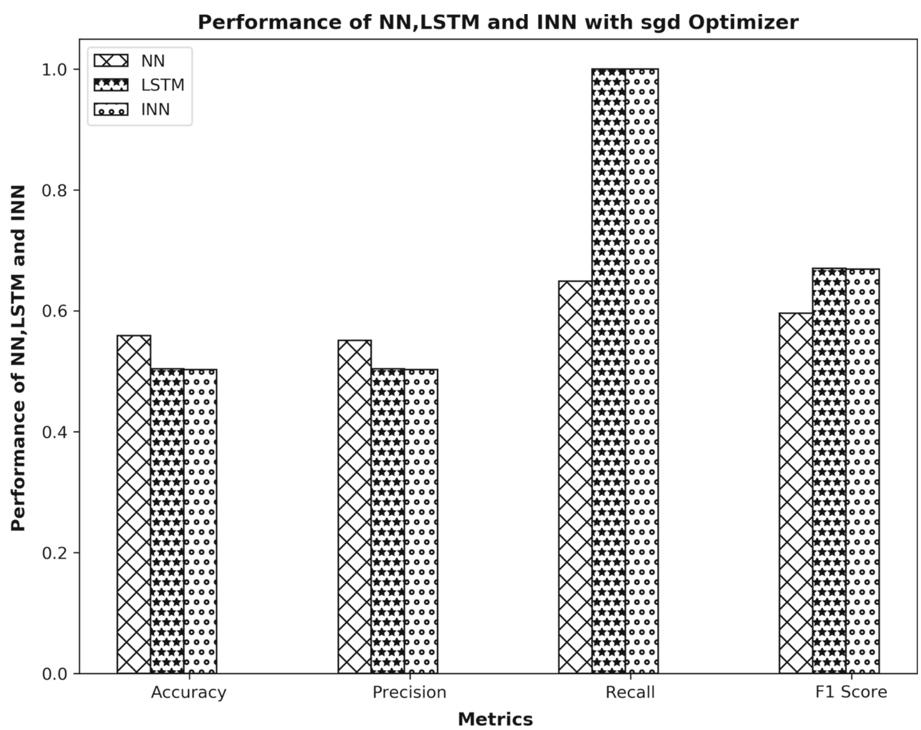


Fig. 15 Performance of neural network (NN), LSTM and improved NN with sgd Optimizer

Improved NN gives better accuracy, recall and F1 score compared to other architectures with adagrad optimizer. However, LSTM gives better precision with adagrad optimizer. NN gives better recall and F1 score compared to LSTM with adagrad optimizer.

Figures 19, 20, 21, 22 and 23 show NN, LSTM and INN performance with various loss models. Figure 19 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with binary entropy loss model. Binary cross-entropy loss model gives better accuracy, precision, recall

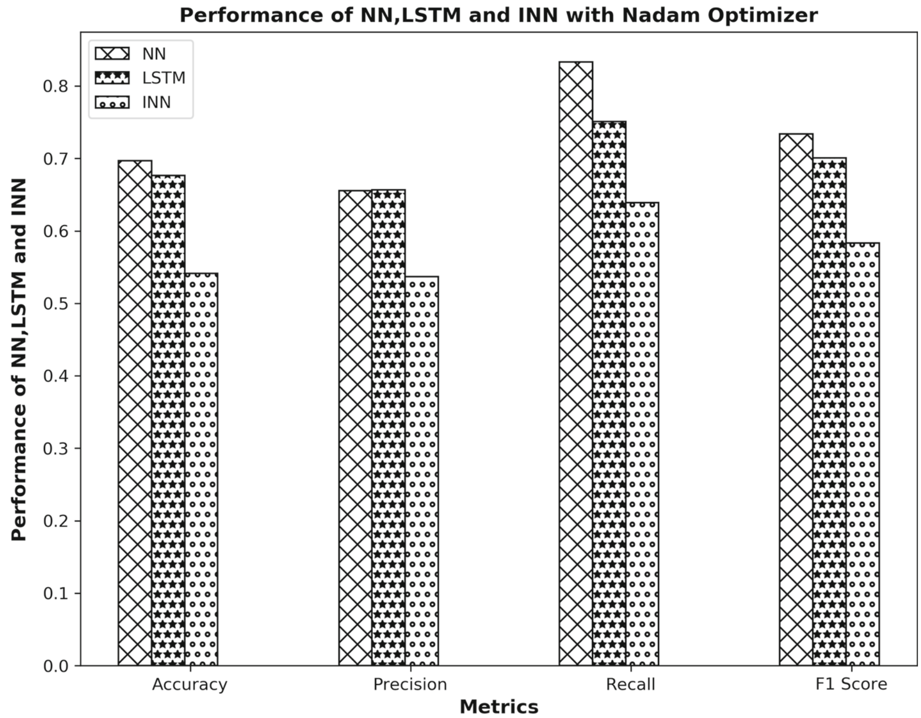


Fig. 16 Performance of neural network (NN), LSTM and improved NN with Nadam optimizer

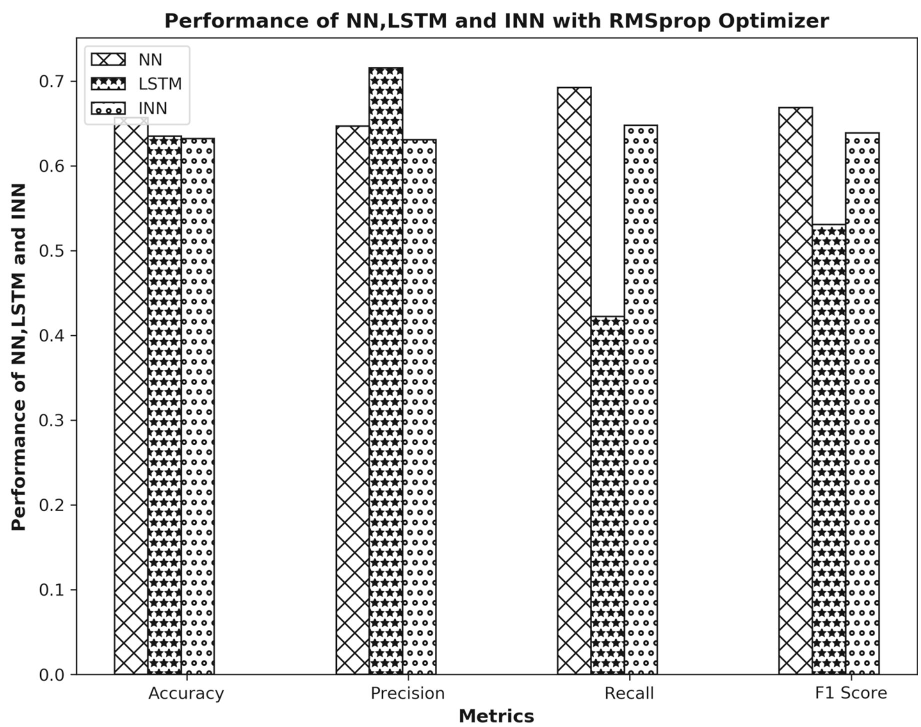


Fig. 17 Performance of neural network (NN), LSTM and improved NN with RMSprop optimizer

and F1 score in INN compared to other architectures. Figure 20 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with mean square error loss model. Mean square error loss model gives better accuracy, recall and F1 score in INN compared to other architectures. However, LSTM gives better precision compared to other architectures. Figure 21 shows performance of two-layer NN, two-layer LSTM and four-layer INN with mean squared logarithmic error loss model. Mean squared logarithmic error loss model gives better

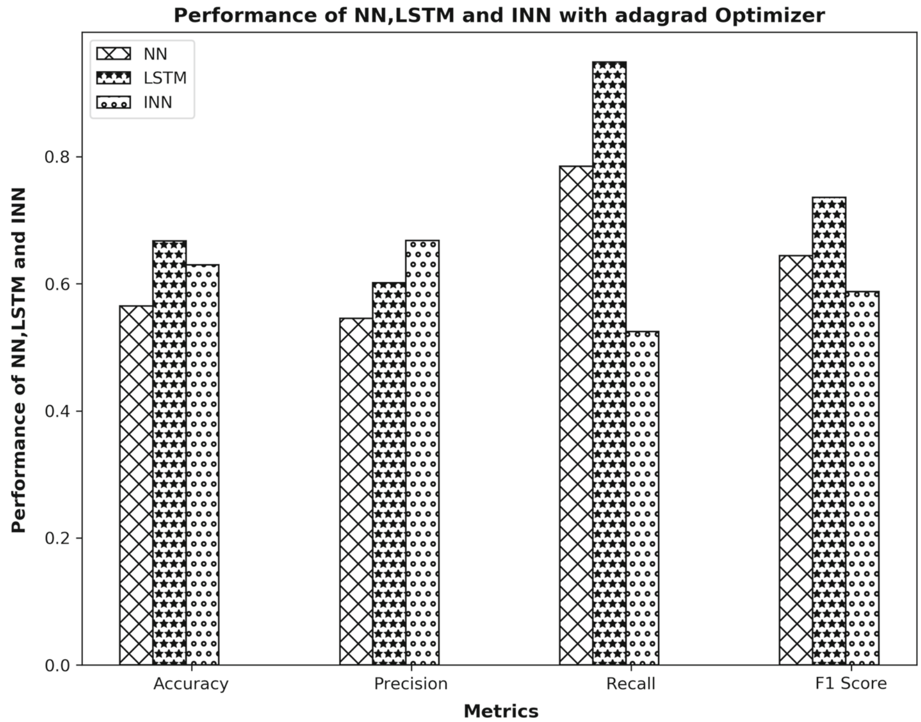


Fig. 18 Performance of neural network (NN), LSTM and improved NN with adagrad optimizer

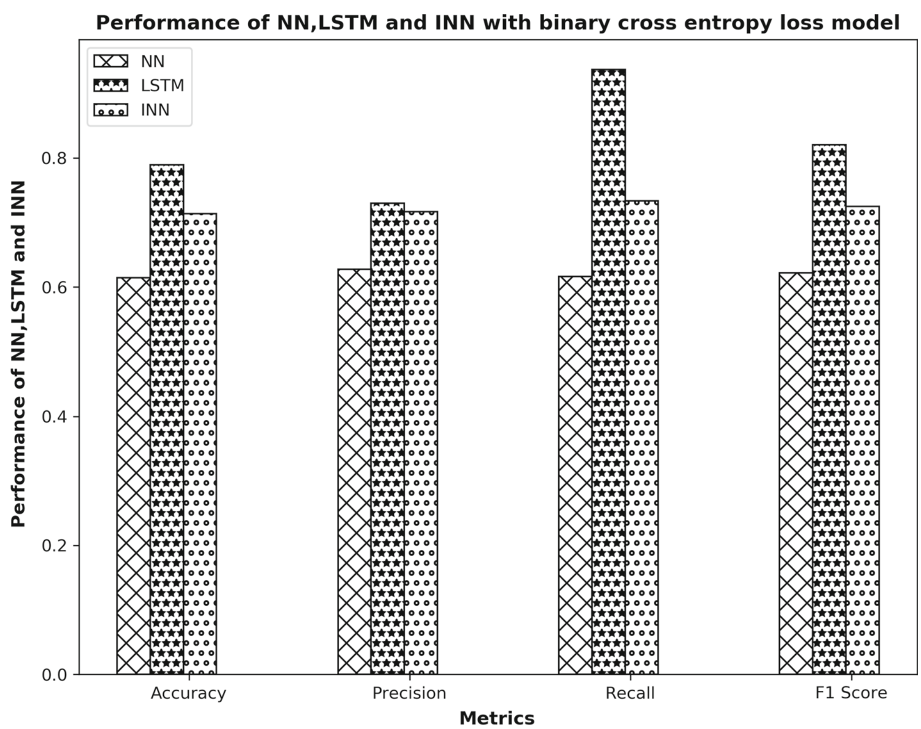


Fig. 19 Performance of neural network (NN), LSTM and improved NN with binary_crossentropy loss model

recall in INN compared to other architectures. However, LSTM gives better accuracy and precision with mean squared logarithmic loss model.

Figure 22 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with categorical hinge loss models. Categorical hinge loss model gives better accuracy, precision in NN compared to other architectures. However, LSTM, INN gives better recall and F1 score compared to NN. Figure 23 shows the performance of two-layer NN, two-layer LSTM and four-layer INN with

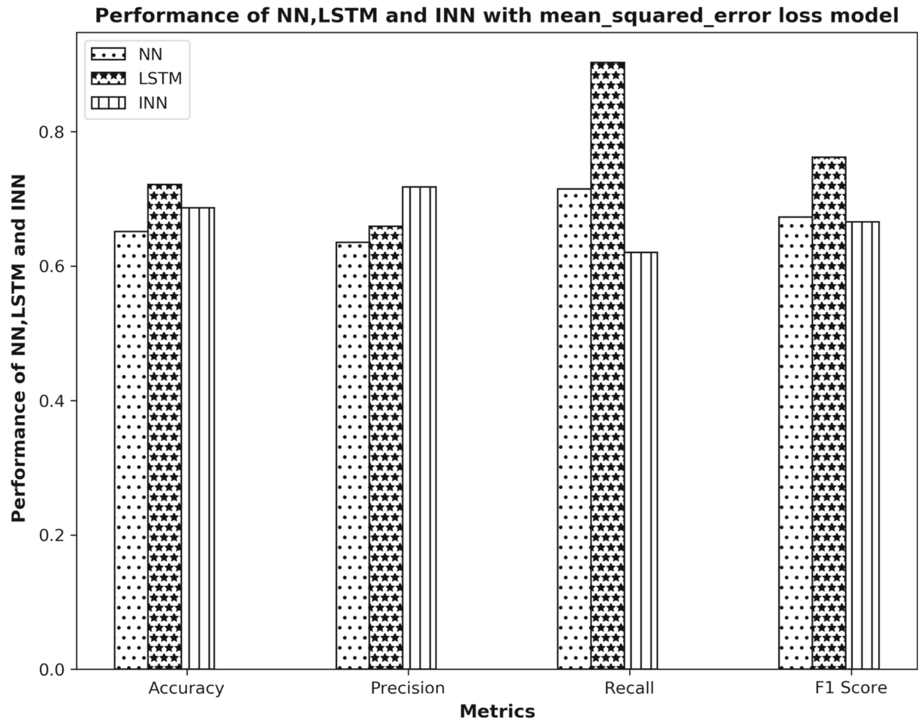


Fig. 20 Performance of neural network (NN), LSTM and improved NN with mean_squared_error loss model

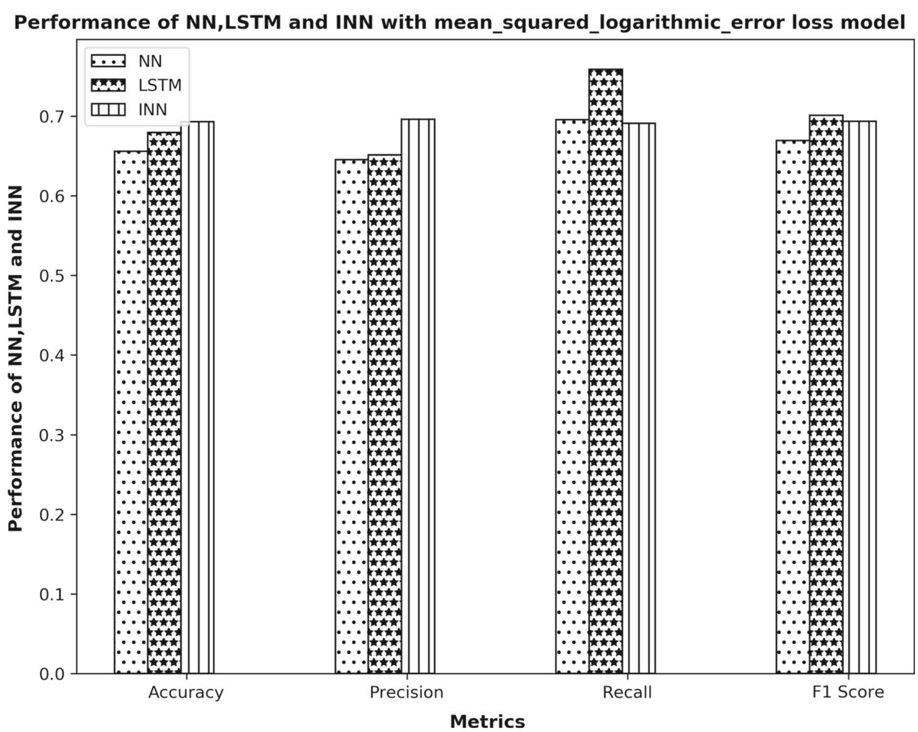


Fig. 21 Performance of neural network (NN), LSTM and improved NN with mean_squared_logarithmic_error loss model

logcosh loss models. Logcosh loss model gives better accuracy, precision, recall and F1 score in INN compared to other architectures. LSTM comes next in the performance followed by NN. Table 9 shows the comparison of proposed INN and LSTM with other works.

6 Conclusion

In this paper, we have analyzed machine learning and deep learning algorithms for EEG signal classification. Conventional SVM and logistic regression techniques along

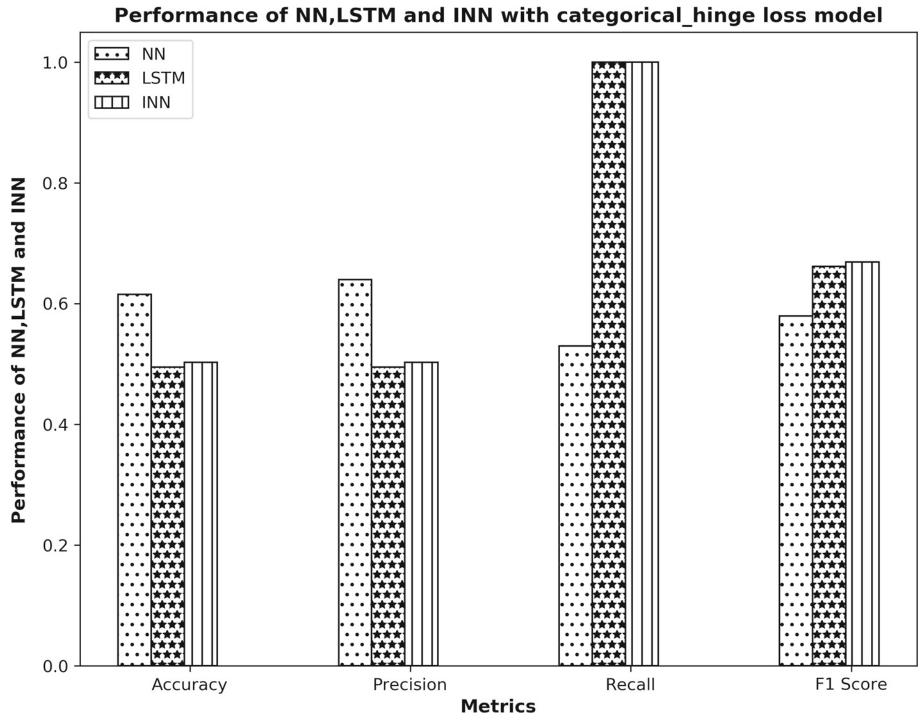


Fig. 22 Performance of neural network (NN), LSTM and improved NN with categorical_hinge loss model

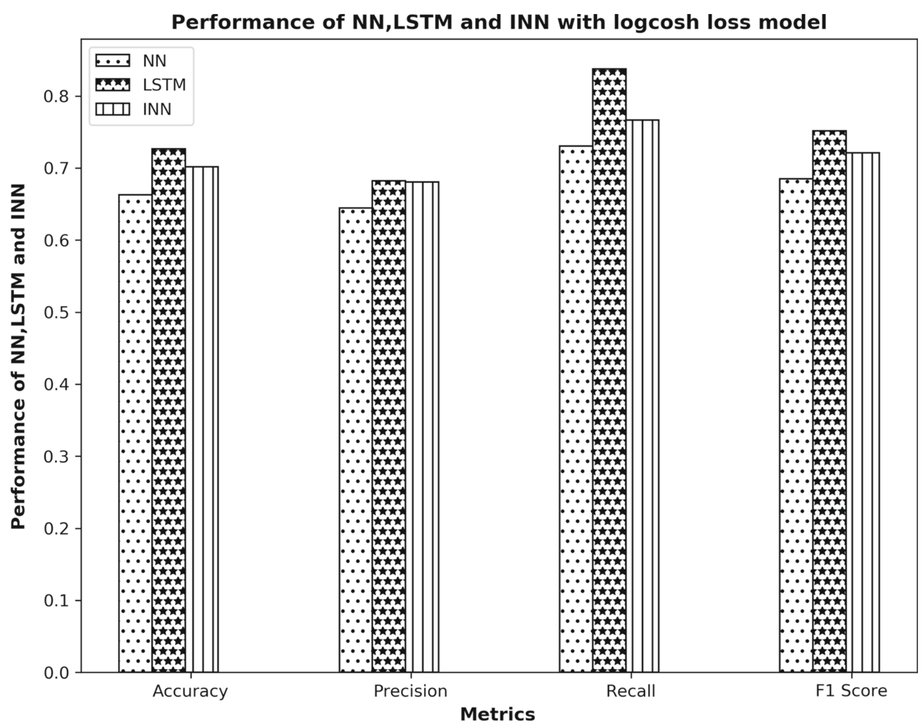


Fig. 23 Performance of neural network (NN), LSTM and improved NN with logcosh loss model

with basic neural network are implemented using Python in keras to check the performances. LSTM and improved NN are proposed for better performance of 71.3% and 78.9% accuracy, respectively, in EEG classification. Using one-dimensional gradient, descent activation function with radial basis function in the initial layers of improved neural network is the novelty that helps in achieving better accuracy, precision, recall and F1 score compared to conventional methods. Simulations are carried out using various activation functions, optimizers and loss models to analyze the performance.

Table 9 Comparison of proposed INN and LSTM with other works

Author/Paper	Year	Database	Algorithm	Number of Layers	Applied	Accuracy (%)
Cui et al.	(2018)	ISRUC-Sleep	DL-CNN	7	Five-way classification	92.2
Michielli et al.	(2019)	Sleep-EDF	DL-RNN with LSTM	5	Five-way classification	86.7
Lajnef et al.	(2015)	–	ML-DSVM	–	Five-way classification	74.74
Lajnef et al.	(2015)	–	ML-LDA	–	Five-way classification	73
Aboalayon et al.	(2016)	PhysioNet Sleep (EDF)	ML-LDA	–	Six-way classification	74.49
This work	–	Bonn Univ	DL-LSTM	1	Two-way classification	71.38
This work	–	Bonn Univ	ML-INN	4	Two-way classification	78.92

Future work can be concentrated in multi-stage LSTM architectures and pooling layers in the proposed INN to increase the performance of deep learning algorithms for EEG signal classification.

Compliance with ethical standards

Conflict of interest Data used for this research are collected from Bonn university database. The authors thank them for this.

Human and animals rights This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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