Original Article

Detection Of Alzheimer's Disease Using ELRFXG Booster And ELCR Machine Learning Algorithms

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Abstract

Image processing and analysis techniques have become more prevalent within the medical field as they aid in the detection, diagnosis and prognosis of conditions that threaten people's lives. Some conditions, however, present additional challenges to medical experts, requiring a further and more advanced examination of the patient's data before a decision can be made. There are many health issues related to brain, Alzheimer disease is one among them. Alzheimer's disease is a chronic condition that leads to degeneration of brain cells leading at memory enervation. Alzheimer's Disease (AD) is the most common dementia affecting cognitive domains such as memory and learning, perceptual-motion or executive function. This Research work uses various steps involved in the image processing to analysis the Alzheimer affected parts of brain MRI. The pre-processing, Image segmentation, Feature extraction and analysing Alzheimer disease are the basic steps followed during the research work. The implementation part of the research work consists of introducing Deep learning concept to find the Alzheimer effected parts of the brain MRI. The proposed ELRFXG and ELCR are useful in finding the Alzheimer effected parts within a fraction of seconds. The proposed model prediction process is accurate compared with the other classification algorithms. The proposed model is compared with other Machine Learning algorithms to test the performance. Machine Learning algorithms such as CNN, RNN, TL, RF, XG-Boost were used for comparison with proposed ELRFXG and ELCR algorithm. The measurement and testing strategy followed for each sample are common for showing transparency in simulation results and testing strategy. The identification process followed in the research work can lead to take preventive measures before the situation becomes worst for the patient.

KEYWORDS: Alzheimer's Disease, Medical Image processing, Neural Networks, Machine Learning, CNN and RNN.

1. Introduction

Alzheimer's disease is one of the diseases that grow rapidly due to the food habits and life style changes around the world. This disease causes a great impact on the regular life of a person by affecting his memory, decision making ability and other cognitive predicaments [1]. Recent statistics show that one in three senior citizens dies due to Alzheimer's or Dementia disease. This ratio is a global threat because it overthrows the sum of breast cancer and prostate cancer mortalities. The lethality rate of Alzheimer's disease is increased by 145% during the last decade [11]. One hopeful virtuous information discovered is that the recovery and the sustainability of this disease is substantially increased if found and treated in earlier stages. This conviction stipulates an immense possibility to carryout ample of research activities regarding detection and prediction of Alzheimer's Disease.

A more reliable way to detect and predict Alzheimer's disease is then established using MRI. The only disadvantage of MRI over other methods is the cost. Yet comparing with the advantages of MRI, the cost expansion is justified well due its more detailed imaging procedure. MRI images can provide more information about the soft tissues of the brain than CT scan images [8][9]. This clear view of the brain tissue makes it possible to detect Alzheimer's disease with increased accuracy, precision, sensitivity and specificity. Thus, MRI images are taken as the core provenance in this work.

This paper is based on the effects of Alzheimer diseases found on the MRI collected from research center for better understanding the severity level of the disease. The Minimal Interval Resonance Imaging in Alzheimer's disease (MIRIAD) is used dataset for testing the presence of Alzheimer disease in MRI, which is owned property of Dementia Research Centre. The usage of MIRIAD dataset in this research work is for testing purpose and training the dataset for working-out with necessary classification model. The technicians working in the filed for finding out the Alzheimer disease needed the information from images or signals.

The ReLU activation functions are very useful rather using automatic activation functions in convolutional neural network. The 30 slices of brain parts are taken for consideration and max pooling operation is carried out for each slice. The different levels of layers are carried out before applying flatten dense 512 ReLU. The level 1, 2 and 3 follows 32 ReLU, 64 ReLU and 128 ReLU respectively in proposed feature extraction model using CNN.

The classifications are made for separate male and female Alzheimer infection ratio calculation. Healthy Patients (HP) and Alzheimer's Disease (AD) were separately classified using proposed CNN model. The proposed feature extraction model is tested and compared with various algorithms such as SVM, Random Forest and KNN. The obtained classified images are taken for final analyzing stage, were The Ensemble Algorithms ELCR(CNN-RNN) and ELRFXG(RF-XG-Boost) were proposed for the identification of the Alzheimer's Disease. The ELCR performs better in detection accuracy.

2. RELATED WORKS

Ibrahim et al [2013] designed a neural network model to identify the tumour in the brain image. They have pre-processed the image using arithmetic mean and used PCA algorithm to extract the feature values. George et al [2012] enhanced their brain image using filtering techniques.Han et al[2016] used a hybrid sequential feature selection approach for the diagnosis of Alzheimer's Disease in Neural Networks Ortiz et al [2016] designed a Ensembles of Deep Learning Architecture for the early Diagnosis of the Alzheimer's Disease[15].

In 2018, Jose et al. provided a review on neuroimaging techniques for brain disorders. It is stated that machine learning techniques can be useful for finding the underlying neurological causes of brain disorders [11]. Pellegrini et al. discussed the machine learning techniques used for dementia and cognitive impairment from 2006 to 2016 in 111 papers[12]. It stressed on the development of novel machine learning models from interdisciplinary approach. Rathore et al.[13] also provided a review on feature extraction and classification of Alzheimer's and its prodromal stages. Pan, Dan, et al 2020 proposed a classifier ensemble developed by combining CNN and EL, i.e., the CNN-EL approach, to identify subjects with MCI or AD using MRI: i.e., classification between (1) AD and healthy cognition (HC), (2) MCIc (MCI patients who will convert to AD) and HC, and (3) MCIc and MCInc (MCI patients who will not convert to AD). For each binary classification task, a large number of CNN models were trained applying a set of sagittal, coronal, or transverse MRI slices; these CNN models were then integrated into a single ensemble[10].

The Pre-processed MRI Images are taken for selecting necessary features, which is very essential for final analyzing part. The proposed CNN model is implemented in collecting necessary features and tested with classification algorithms for accuracy. When considering the accuracy for the proposed CNN model, the ReLu activation function is used for each and every levels of the pooling techniques. The Dropout in the levels are useful in decreasing the count of the filters. The filtering numbers are increased doubling the previous levels of the CNN Model, which is very helpful in extracting the best features. The class formation is carried out for Alzheimer Disease (AD) and Healthy Controls (HD) separately for male and female patient record present in the collected dataset. The final process of the research work is to test for the accuracy, AUC, sensitivity and Specificity for the different learning algorithms.

With the MIRIAD dataset, the work initiated and processed with training data and testing data. The dataset is pre-processed, and the relevant features are extracted and then the classification work is done using the existing algorithms like CNN, RNN, TL, RF, XG-Boost. The Ensemble Algorithms ELCR(CNN-RNN) and ELRFXG(RF-XG-Boost) were proposed for the identification of Alzheimer's Disease. The ELCR performs better in detection accuracy.

3. Pre-processing

The brain MRI is basically three-dimensional images, which must be converted into two dimensional images for better analyzing through image processing. The size conversion is also carried out for better recognition during the pre-processing stage and other stages. The common 512 X 512, 128 X 128 and 256 X 256 size alterations are made into the collected images. The 512 is best suitable size for applying image processing and finding out the abnormal one.

A. Alzheimer MRI Dataset

The Brain MRI collected from MIRIAD is basic dataset collected from the Dementia Research Centre, which contains total 69 persons MRI images divided into two separate groups. The group 1 has information of Healthy Patients (HP) and second group consist of 46 patients who are affected with Alzheimer's Disease (AD). The basic classifications of the dataset are divided into binary classifications. This research works examines the applications of proposed CNN model with considering these classes. The research work also focuses to category the collected MRI with male and female affected patients records with significant difference.

The MIRIAD MRI Brain scanned images, which is very hug in numbers. The dataset consists of Alzheimer's disease effected patients and healthy elderly peoples[30]. The collected record set has the data of different patients from range 2 weeks to two years of the severity level. The data collected from various patients are useful in analyzing and giving the ranges between the male and female Alzheimer effected peoples.

The collected MRI brain images are in the format of three-dimensional images, such three-dimensional images are to be converted into two dimensional images for image convenient way of analysing Alzheimer diseases. The multiple overlapping technique can be useful for solving many e irrelevant object presence in MRI brain images. the slices of brain were made for easy e identification process of Alzheimer diseases. Each and every slices of brain thickness is calculated and converter to smaller pieces of length 5cm. The colour differences presence on the MRI brain images are to be identified with various pre-processing technique followed in image processing. the basic smoothening technique and identification of different objects' presence on the brain images are carried out perfectly in pre-processing technique and the collected preprocessed image is sent for identifying the necessary pictures.

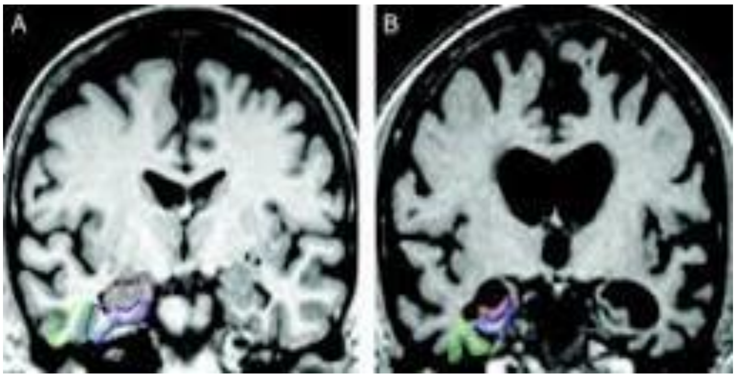

Figure. 1. Brain MRI of Alzheimer infections

The MRI images collected on the data base is divided into four categories based on the severity level of Alzheimer disease. The identified classes on the dataset are divided into testing and training sets.

- Mild Demented
- Moderate Demented
- Non-Demented
- Very Mild Demented

Table. 1. Alzheimer classes on training and testing dataset

Dataset	Mild Demented	Moderate Demented	Non-Demented	Very Mild Demented
Overall	896	64	3200	2240
Training	717	52	2560	1792
Testing	179	12	640	448

Table 1 clearly shows the variations in different classes of Alzheimer Diseases. Each four classes were divided into a training and testing set which is preprocessed and taken for feature extraction.

B. Detection and Prediction parameters for ELCR and ELRFXG(RF-XG-Boost) DETECTION

The confusion matrices play a major role in evaluating the proposed ELCR and ELRFXG(RF-XG-Boost) classifiers. The True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are the measurement considered for finding the best classifier among various existing classifiers. The record set if divided into training and testing for applying the detection and prediction process of Alzheimer disease. 10% of the acquired data is considered for measurement using confusion matrices. Based on the performance of proposed model during confusion matrices, Accuracy, Precision, Sensitivity, Specificity and F-Score are calculated. This performance analysis is not only carried out for detection, it also used for calculating the prediction process. The time taken for evaluation process is also calculated to find the best supporting model.

4. Proposed Ensemble model of CNN and RNN convolutions (ELCR)

The ensemble of CNN and RNN is constructed in a way that the process of kernel queue selection is optimized through RNN which is supplied to the convolution processes of CNN. Here CNN performs the classification process. The RNN LSTM Architecture is given in Figure 2.

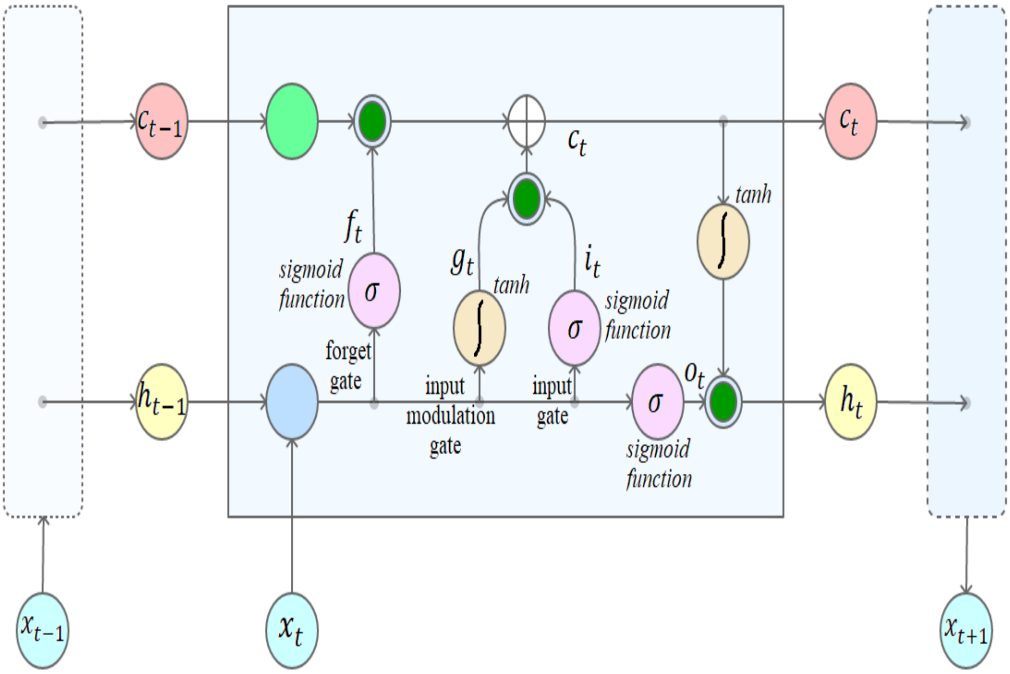

Figure 2: LSTM RNN

In figure 2, x_{t+1} refers current input image segment. For that input image segment, a suitable Kernel Queue K_s is chosen from the kernel superset λ based on the past knowledge acquired during x_t and x_{t-1}. Thereby the optimum kernels for the CNN convolutional filters are supplied by RNN. The ELCR Architecture diagram is given in Figure 3.

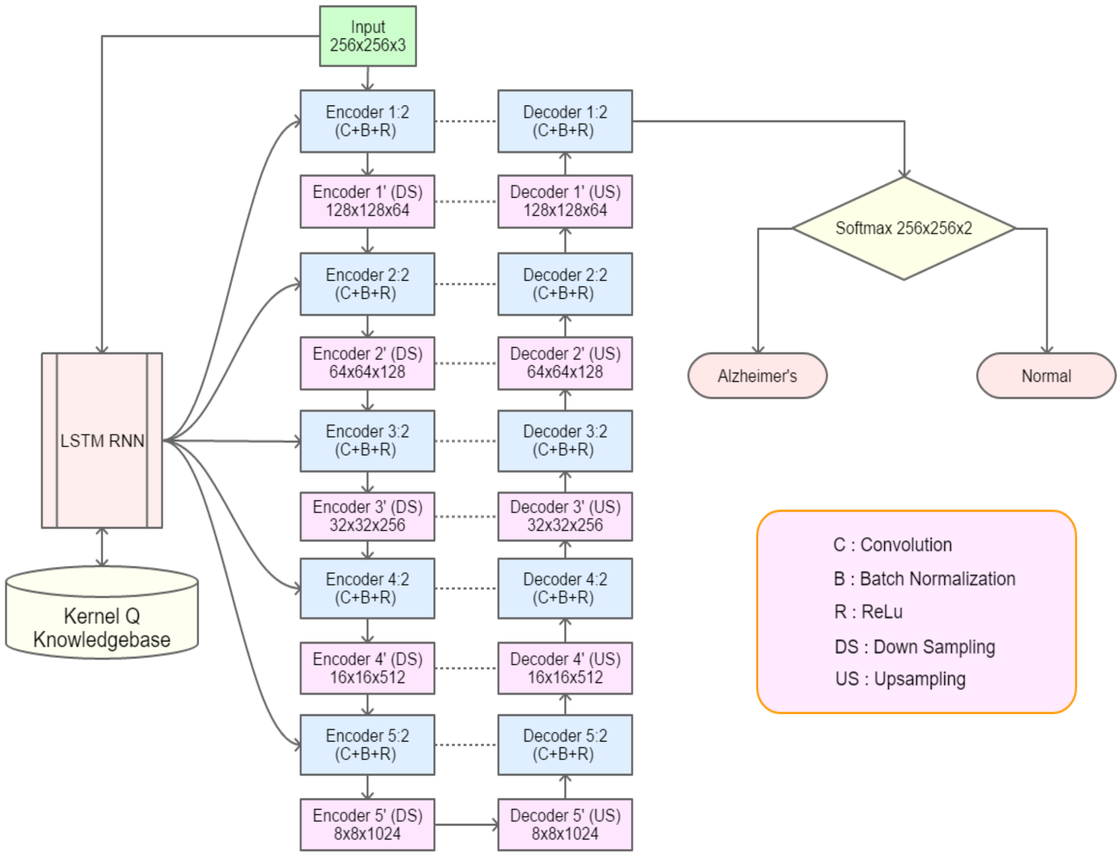

Figure 3: ELCR Architecture

The malicious brain portions are detected from the MRI image using ELCR. The prediction process is performed based on the incremental changes of the malignant portion. A fuzzy decision-making method is applied to the prediction model to consummate the severity into low, medium, and high categories. Let δ_p be the size of the malignant portion found in the previously taken MRI image and δ_c is the size of the malignant size in the current MRI. The unit of δ_c and δ_p are represented in pixels. The difference between the sizes δ_d is calculated by subtracting the size of the malignant portion of the previous MRI from the current size.

$$\delta_d = \delta_c - \delta_p \qquad \text{Equation (1)}$$

For prediction, a risk factor equation is derived based on Fuzzy Decision Model (FDM) by using annotated training data as follows

$$\rho = \left(\frac{1}{\delta_c} \times \frac{\delta_d}{d}\right) \qquad \text{Equation (2)}$$

where d is the time difference between the scans in days

The severity is labeled using the following Equation

$$\text{Severity} = \begin{cases} \text{low if } \rho =< \frac{1}{3} \\ \text{medium if } = \frac{1}{3} \leq \rho < \frac{2}{3} \\ \text{high if } \rho \geq \frac{2}{3} \end{cases} \qquad \text{Equation (3)}$$

5. PROPOSED ENSEMBLE MODEL OF ELRFXG(RF-XG-BOOST)

The ensemble technique followed for identifying the Alzheimer disease at early stage is mostly considered to be the most difficult part of the research. The techniques used previously produces better result in finding out the Alzheimer affected parts but takes little extra time in correlating the result. The random forest algorithmic technique used previously are useful in finding the Alzheimer affected parts from overall brain MRI images.

The convolution neural network and recursion neural network used in the existing works are very helpful in classifying the healthy region of the brain from unhealthy or Alzheimer affected parts. The regions are converted into white and black combinations and identified with those classification methods. The convolution methods used in the process of classification is very useful in categorizing the affected parts from the unaffected parts of the brain. The level differences created for each divided pixel are collected and activated with automatic activation function in existing works. The activation functions used previously are lack in fixing the exact parameters for the evaluating the density level of the patches found in the images[15].

The proposed model ELRFXG uses all the combinations of the existing algorithms and produces better result in time consuming manner. The convolution methods used for the classification of healthy and unhealthy parts of the Alzheimer disease images uses a specific way of fixing parameter setting, which is a novel approach in activation or trigger function. The application of random forest algorithm is very useful in consolidating the training and testing sets collected from the Alzheimer dataset. The decision tree mechanism followed for predicting the perfect ensembled record are most critical part implemented along with convolutional method.

The random forest implementation on proposed ELRFXG model plays a key role in merging the different formation of trees together to acquire the prediction classes from the Alzheimer dataset. In some cases, there is a probability chance of not producing a perfect output for the Alzheimer affected predictions. In most of the cases the perfect results are obtained for identifying the healthy and unhealthy parts of the Alzheimer affected parts from the collected data only when the actual values presented in the feature variables of the dataset is classified accurately during the prediction procedure and predictions should happen with low correlation rate for each tree formations.

The discussed issues faced in previous methodologies are resolved in proposed ELRFXG model by using a convolutional method in activating the function in various levels. The parameter set for the activation function is considered with manual setting for better accurate processing. The decision tree prediction corrections are made for each level and obtained errors are corrected then and there.

The Gradient boosting tree technique followed in the prediction process are helpful in combining the weaker models together to produce the best and strong models in prediction procedure. Usually, performances of the XGBoost algorithm are strong in machine learning algorithms and with supervised technique. The usage of XG Boosting can reduce the ranking problem happens during the decision making in prediction stage, multiclass problems in various levels and regression problem during classification stages.

The combinations of the XG Booster algorithm with convolutional activation function parameter setting is mostly helpful in proposed ELRFXG algorithm for producing accurate prediction result. The manual parameter setting in activation function for convolutional level are very much needed for accurately setting the measurement, which creates a gateway in producing a better prediction procedure.

6. Results and Discussion

Most of the research work aims to justify in satisfying the accuracy of the proposed model in validating.

A. Performance Analysis based on Accuracy

The accuracy score is very useful in determining the quality of the proposed model for finding the Alzheimer effects. If the proposed classification model accuracy is high, it is considered as best algorithm. The accuracy is calculated with the following equation 4.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad 4$$

The accuracy of the proposed ELCR is calculated based on the detection and prediction based on the confusion matrices. Table 6.14 discusses about the detection value and Table 6.15 discusses about the prediction value of the proposed ELCR model.

Table 6 Detection Accuracy of ELCR

Detection Accuracy				
Data	**CNN**	**RNN**	**TL**	**ELCR**
10	56.8015	56.99204	56.71395	58.07444
20	68.625	66.29166	67.66667	70.20833
30	74.86756	72.30159	73.45486	77.55307
40	80.28184	75.96629	77.99438	82.59222
50	84.06133	79.02574	81.4279	86.56554
60	87.1494	81.64288	83.90758	90.02031
70	89.80199	83.82684	86.37572	92.51512
80	91.56368	85.43259	88.3221	95.01779
90	93.97529	87.2778	90.44577	97.28172
100	95.63483	88.65871	92.00562	99.03277

The detection accuracy for the existing CNN, RNN and TL classifiers are compared with proposed ELCR classifier in Table 6. The data collected are divided into various groups as mentioned in the table. The generated result is very clear to show that the proposed ELCR performance is much better than other existing classifiers.

Table 7. Prediction Accuracy of ELCR

Prediction Accuracy		
Data	**TL**	**ELCR**
10	56.65313	57.46152
20	67	69.97501
30	73.03524	77.20764
40	77.26355	81.94682
50	80.85791	86.0897
60	83.67378	89.01279
70	85.90079	92.10584
80	87.86043	94.29364
90	89.66736	96.07877
100	91.24646	98.01985

The prediction accuracy of the proposed classifier is tested with Transferred Learning (TL) with various data groups formed. The reason of considering only TL for comparing with proposed ELCR is because of biggest margin in other existing algorithms. Each data groups are tested for prediction accuracy and proposed ELCR shows the best result compared with TL.

Based on the observed results, proposed ELCR scored 99% accuracy value which is 3.5% higher than the nearest achievement of CNN. Similarly, in prediction process, ELCR secured 98% accuracy whereas the TL Method scored 91.24%. Based on the accuracy parameter, it is understood that the ELCR method performed better than other methods.

B. Performance Analysis based on Precision

The performance of the proposed ELCR classifier is tested for the tidiness in the measurement, which can be possible with the precision calculation. The performance of the proposed ELCR is more when the precision is high and falls very low when the precision is low. The equation used for the precision calculation is given bellow5.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad 5$$

The performance of the proposed ELCR in the detection process is calculated in the table 8. The precision values are taken for the existing algorithms with proposed ELCR classifier.

Table 8. ELCR Detection rate using Precision

Detection Precision				
Data	**CNN**	**RNN**	**TL**	**ELCR**
10	56.59316	57.03371	56.54728	57.9911
20	68.75	66.41666	67.75	70.41666
30	74.86756	72.21825	73.24653	77.71974
40	80.15684	76.21629	78.28605	82.5089
50	84.26966	78.81741	81.26123	86.81554
60	87.35773	81.35121	83.94924	89.97864
70	89.63532	83.82684	86.37572	92.72346
80	91.48034	85.59925	88.5721	94.68446
90	93.97529	87.4028	90.36243	97.28172
100	95.75983	88.95037	92.04729	99.32444

The observations show that the ranking order of the examined methods is ELCR, CNN, TL and RNN given in best first order. ELCR achieved the highest detection precision value 99.32%. The CNN secured next high precision value of 95.76%.

Table 9 Proposed ELCR prediction measurement using precision

Prediction Precision		
Data	**TL**	**ELCR**
10	56.63811	57.69162
20	66.6	69.8
30	72.78899	77.09837
40	76.97856	81.82505
50	80.62621	86.08324
60	83.08421	88.95674
70	85.70713	91.91809
80	87.27379	94.1001
90	89.2732	96.08844
100	90.50478	97.69162

The prediction range of the proposed ELCR is measured with precision and achieved 97.69% which is higher than the TL's prediction precision score of 90.5% as in table 9.

C. Performance Analysis based on Sensitivity

The calculations made for recall of true positive error rate are often called as Sensitivity measurement. The measurement taken for the existing classifiers are compared with the proposed ELCR for sensitivity equation 6

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \qquad 6$$

The sensitivity of the proposed ELCR classifier refers to the number of correctly classified information out of all other records. This is also a direct proportional parameter with the quality of a classification algorithm. The obtained range of values for detecting process is shown in the table 10.

Table 10 Proposed ELCR Detection analysis based on Sensitivity

Detection Sensitivity				
Data	**CNN**	**RNN**	**TL**	**ELCR**

10	56.82996	56.98622	56.7364	58.08792
20	68.57855	66.25104	67.63727	70.12448
30	74.86756	72.33882	73.55299	77.46153
40	80.35773	75.83711	77.83202	82.64664
50	83.92	79.14719	81.53301	86.38363
60	86.99525	81.82855	83.87935	90.05368
70	89.9351	83.82684	86.37572	92.33872
80	91.63306	85.31487	88.13144	95.31992
90	93.97529	87.18484	90.5133	97.28172
100	95.52103	88.43451	91.97064	98.74841

The prediction procedure followed in the proposed ELCR is measured with sensitivity and obtained result is discussed in table 11.

Table 11. Proposed ELCR Prediction analysis based on Sensitivity

Prediction Sensitivity		
Data	**TL**	**ELCR**
10	56.65512	57.42733
20	67.1371	70.04516
30	73.14925	77.26724
40	77.41983	82.02481
50	81.00157	86.09436
60	84.07558	89.05656
70	86.04038	92.26453
80	88.3099	94.46575
90	89.98255	96.06984
100	91.8675	98.33716

The proposed ELCR prediction accuracy is high compared with other classifiers. The grouping of the data for TL and ELCR are compared for each data sections. The highest range of the proposed ELCR is observed 98.3%, where the same group of the TL has 91.8% as accuracy. The lowest point of accuracy is observed at the first set of data in both the TL and ELCR classifier. The prediction sensitivity of ELCR is 98.33% which is 6.47% higher the value of TL's 91.87% prediction sensitivity.

D. Performance Analysis based on Specificity

The true negative rate of the proposed ELCR classifier is measured using specificity using the following equation 6.4. The calculated range gives an idea of difference between the existing classifiers with the proposed ELCR classifier.

$$\text{Specificity} = \frac{\text{TN}}{\text{FP+TN}} \quad 7$$

High specificity indicates the high quality of a classification algorithm. The calculated specificity values of the detection methods are given in Table 12. The prediction specificity values are given in Table 13

Table 12. Proposed ELCR Detection rate using specificity

Detection Specificity				
Data	**CNN**	**RNN**	**TL**	**ELCR**
10	56.77327	56.99787	56.69165	58.06101
20	68.67168	66.3325	67.69616	70.29289
30	74.86756	72.26448	73.35754	77.64523

40	80.20632	76.09678	78.15864	82.53799
50	84.20384	78.90531	81.32349	86.74929
60	87.30483	81.45937	83.93586	89.98698
70	89.66976	83.82684	86.37572	92.69302
80	91.49451	85.55109	88.51467	94.71966
90	93.97529	87.37123	90.37847	97.28172
100	95.7492	88.88554	92.04065	99.32048

The prediction range of the proposed ELCR is measured with precision and achieved 97.70% which is higher than the TL's prediction precision score of 90.64% as in the table 13. The comparison made between the TL and ELCR shows very close rage in values acquired for many groups of collected data as shown in 6.20.

Table 13. Proposed ELCR Prediction rate using specificity

Prediction Specificity		
Data	**TL**	**ELCR**
10	56.65113	57.49601
20	66.86508	69.90533
30	72.92234	77.14831
40	77.10903	81.8692
50	80.71558	86.08504
60	83.28135	88.96911
70	85.76228	91.94833
80	87.42137	94.12285
90	89.3571	96.08769
100	90.64357	97.70667

The results explicitly show that the detection and prediction specificity of the proposed ensemble of CNN + RNN is improved than the standalone CNN or RNN. Regular CNN secured the specificity score of 95.75% and the score of the regular RNN is 88.88%. The ensemble of CNN + RNN produced a better specificity score value of 99.32%. The specificity of Transfer Learning is computed as 92.04%. While perceiving the prediction specificity, ELCR acquired the value 97.71% whereas TL acquired 90.64%. These observations evidently demonstrate that the ensemble of two convolutions can produce more specificity performance.

E. Performance Analysis based on F-Score

F-Score refers the balance between the precision and recall. The F-Score is a single entity that reveals the combinational properties of precision and recall. It is also a directly proportional element that shows the quality of a classification algorithm. F-Score is also known to be F-Measure calculated using the equation 8.

$$\mathrm{F-Score} = \frac{2}{\frac{1}{\mathrm{Presision}}+\frac{1}{\mathrm{Recall}}} \qquad 8$$

F-Score values for detection is given in Table 6.21 and prediction F-Score values are tabulated in Table 14.

Table 14. Proposed ELCR Detection rate using F-Score

Detection F-Score				
Data	**CNN**	**RNN**	**TL**	**ELCR**
10	56.71132	57.00995	56.64169	58.03947
20	68.66417	66.33375	67.69359	70.27027
30	74.86756	72.2785	73.39944	77.59042

40	80.25716	76.02622	78.05837	82.57771
50	84.09446	78.98196	81.3969	86.59905
60	87.17612	81.58918	83.91428	90.01614
70	89.78496	83.82684	86.37572	92.53069
80	91.55663	85.45683	88.35122	95.00113
90	93.97529	87.29368	90.43781	97.28172
100	95.64028	88.69168	92.00895	99.03558

The simulation results are clear in explaining F-Score values of ELCR, CNN, TL and RNN are 99.04%, 95.64%, 92% and 88.69% given in high-to-low performance order. A performance improvement of 3.4% is accomplished by the ensemble than the CNN in terms of F-Score. This high F-Score discloses that the balance between the precision and recall is preponderantly maintained in the CNN+RNN ensemble.

Table 15. Proposed ELCR Prediction rate using F-Score

Prediction F-Score		
Data	**TL**	**ELCR**
10	56.64662	57.55917
20	66.86747	69.92237
30	72.96868	77.18271
40	77.19856	81.92481
50	80.81346	86.0888
60	83.57697	89.00662
70	85.87344	92.09099
80	87.78879	94.28256
90	89.62647	96.07914
100	91.18104	98.01332

ELCR achieved the prediction F-Measure Value of 98.01% which is 6.83% higher than the prediction F-Measure value 91.18% of TL. The comparison graphs for F-Score are given below.

F. Average Processing Time

Processing time is one of the vital parameters in real-time mission critical application. A good classification algorithm should perform swifter with higher accuracy. The Average Processing Time is measured using the bellow equation 9.

$$\text{Average Processing Time} = \frac{1}{n}\sum_{i=1}^{n} \tau_c - \tau_a \qquad 9$$

where n is the number of observations, τ_a is the task arrival time and τ_c is the task completion time. In general, average processing times are noted in mS units (milli Seconds). The measured average processing times for detection of Alzheimer's disease using discussed methods are given in Table 16. Average processing time for prediction is given in Table 16.

Table. 16. Detection Average Processing Time for proposed ELCR

Detection Average Processing Time (mS)				
Data	**CNN**	**RNN**	**TL**	**ELCR**
10	1828	1583	1375	2033
20	1818	1591	1372	2026
30	1829	1588	1365	2014
40	1814	1587	1384	2030
50	1818	1565	1365	2015

60	1815	1569	1385	2021
70	1826	1566	1370	2027
80	1838	1585	1385	2033
90	1831	1586	1369	2013
100	1822	1570	1366	2014

As per the observed results, it is understood that Transfer Learning outperforms other methods in terms of processing speed. The minimum average processing time of 1365mS is achieved by TL while processing the 3rd data chunk. The processing time of ELCR is 2022 on average which is slightly higher than the processing time 1824mS of standalone CNN.

The total average processing times for CNN and RNN individually is calculated by adding them which yields the value 3402.9mS. While comparing the total average processing times for CNN and RNN individually, the time consumed by ELCR is solely 2022.6mS.

Table. 17. Prediction Average Processing Time for proposed ELCR

Prediction Avg. Processing Time (mS)		
Data	**TL**	**ELCR**
10	1364	2008
20	1364	2005
30	1388	2027
40	1365	2026
50	1377	2020
60	1380	2024
70	1382	2017
80	1364	2014
90	1370	2019
100	1381	2033

The Average Processing Time for prediction of ELCR is 2019.3mS which is higher than TL's average processing time 1373.5mS. The increase in processing time could be excusable while comparing the boost in all other performance metrics.

G. Comparison between existing and proposed ELRFXG Algorithm with Learning Algorithm

Here Detection and explains the ELCR, ELRFEG approach which is based MIRIAD datasets and performs better than the existing methods. The Dataset consists of 708 patient records. Detection parameters such as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) are measured for the given data. Based on the measurements, performance metrics such as Accuracy, Precision, Sensitivity, Specificity and F-Score are calculated for detection processes. Average processing time is also measured for the methods. The tabulated values and plotted graphs for existing and proposed methods are discussed in this section.

Table 18: Comparison between existing and proposed ELRFXG Algorithm

Algorithms	Accuracy	Precision	Sensitivity	Specificity	F-Score	Ap time(ms)
RF	87.67	87.75	87.62	87.73	87.68	1896
XG-BOOST	93.74	93.85	93.63	93.84	93.74	1340
TL	92	92.04	91.97	92.04	92	1366
ELRFXG	95.9	96.23	95.59	96.21	95.91	2464

Table 18 illustrates the proposed ELRFXG algorithm that is compared with the RF, XG-Boost and Transfer Algorithms. By calculation the proposed ELRFXG algorithm attains better accuracy and F-Score.

H. Comparison between existing and proposed ELCR Algorithm with Classification Algorithm

Table 19: Comparison of existing and proposed ELCR Algorithm

Algorithms	Accuracy	Precision	Sensitivity	Specificity	F-Score	Ap time(ms)
CNN	95.63	95.75	95.52	95.74	95.64	1822
RNN	88.65	88.95	88.43	88.88	88.69	1570
ELCR	99.03	99.32	98.74	99.32	99.03	2014

Table 19 illustrates the proposed ELCR algorithm that is compared with the CNN and RNN Classification Algorithms. By calculation the proposed ELCR algorithm attains higher accuracy and F-Score.

I. Comparison between the Proposed ELCR and ELRFXG Algorithms

Table 20: Comparison between the Proposed ELCR and ELRFXG Algorithms

Algorithms	Accuracy	Precision	Sensitivity	Specificity	F-Score	Ap time(ms)
ELCR	99.03	99.32	98.74	99.32	99.03	2014
ELRFXG	95.9	96.23	95.59	96.21	95.91	2464

The Collected Datasets are applied with the Existing Algorithms and by analysing the results, it is observed that the Ensemble of ELCR(CNN-RNN) performs good when compared to the other Algorithms. The Accuracy obtained by ELCR for detection is 99.03%. It is also observed that the Ensemble Learning Algorithm consumes a little higher processing time for detection. While comparing the improvement in all other performance metrics, the small increment in processing time could be justified and it will be reformed in the future works. So, Enhanced Ensemble Learning is proposed to overcome the drawback.

7. CONCLUSION

Alzheimer's Disease detection through MRI image processing is one such inceptive research area. This process requires a flawless procedure to process the MRI images witch higher accuracy and precision. There are a few standalone machine learning procedures applied in this research genre. This work is aimed to blend two different machine learning classification procedures to carry out the objective with more accuracy and precision. An Ensemble of RF and XG-Boost and ensemble of CNN and RNN methods are introduced here with appropriate pre-processing methods to the performance betterment. As per the observed experimental results, it is evident that the harmony between the CNN and RNN methods bring forth the ameliorate results than the existing and the other Proposed algorithm ELRFXG. It is also observed that the proposed ELCR and ELRFXG methods consumes a little higher processing time for detection. While comparing the improvement in all other performance metrics, the small increment in processing time could be justified and it will be reformed in the future works.

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