A Novel Approach to Image Classification for Detecting Abnormalities in Neuroimages based on the Structural Similarity Index Measure

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ABSTRACT

Medical imaging has improved image quality and enables accurate diagnosis and treatment. Medical imaging is used in the early detection and diagnosis of mental disorders or mental illnesses, and treatment. This study performs image-based classification using the Structural Similarity Index Measure (SSIM) to detect normal and abnormal neuroimages. Two experiments were performed on the same dataset. 342 Dicom images were divided into standard and abnormal categories. At first, the SSIM between images was calculated. SVM, KNN, Naïve Bayes, and Decision Tree classifiers were applied and compared. Similarly, an artificial neural network using two optimizers, Adam and SGD, was applied to the same dataset. In theexperiments, 100% and 97% accuracy was achieved in image-based classification, while SSIM-based classification achieved 100% and 61% for different classifiers.

Keywords-artificial neural network; Structural Similarity Index Measure(SSIM); medical imaging

I. INTRODUCTION

Neuroimaging is proliferating and is receiving attention from scientists. With the help of neuroimaging techniques, it is easy to investigate the normality and abnormalities of various parts of the human brain [1]. The brain is the central nervous system and a sensible and decisive part of the human body. It controls all human movements, handles situations, makes decisions based on perception, thought, experience, and emotions, and behaves accordingly. Any injury or impairment can alter and imbalance brain functioning [2]. Many years ago, exploring the neurophysiological process or experiments were not allowed on humans, and it could be carried out only on animals [1]. Today, medical imaging has become an exciting field for scientists. Non-invasive techniques, such as functional Magnetic Resonance Imaging (fMRI), Electroencephalogram (EEG), and Positron Emission Tomography (PET), offer various opportunities to diagnose mental illness or impairment [3].

Due to changes in human lifestyles and competitive environments, psychiatric problems, depression, and mental disorders are increasing more and more day by day. Magnetic and functional resonance imaging helps to study the various brain structures and functions and provides new concepts to diagnose cognitive impairments or mental diseases [3]. Many scientists are investigating medical image analysis and identification to improve technology and help physicians decide the cause and treatment in a very short period [4]. Nowadays, this field utilizes computer vision, human-computer interaction, Artificial Intelligence (AI), and Machine Learning (ML) to automate medical imaging analysis and predict quick and correct results. This extraordinary growth is used to automate different types of clinical practice and disease diagnosis using AI [5].

Artificial Neural Networks (ANNs) are a subcategory of ML inspired by the brain. An ANN takes the input data and applies a suitable supervised or unsupervised algorithm to improve itself [6, 7]. ANN is a classification algorithm that automatically extracts and analyzes features from images. The Structural Similarity Index Measure (SSIM) is a novel tool that avoids preprocessing and minimizes classification error [8]. In [9], image quality assessment was performed using SSIM with a neural network. The primary objective was to invent a mechanized IQA tool to detect motion artifacts from brain MRIs. When brain MRIs are acquired, noise or motion is detected. Two images are required to calculate the SSIM, the original and the corrected one. After comparing the artificial with the original image, SSIM is calculated to be used for further analysis using a neural network. Classification with ResNet-18 for three classes achieved the best accuracies of 97%, 95%, and 89% [9].

The study in [10] focused mainly on the pixel-wise loss of reconstructed images. The original image was compared with a reconstructed or textual-generated image using SSIM and three comparison functions: luminance (l), contrast (C), and structure (S). This study used MS-SSIM, MAE, and MSE to reduce the loss of images, and MS-SSIM achieved better results than the other methods. Then, a convolutional autoencoder was used for the images, and after encoding and decoding, the feature vector was obtained. The three different loss functions, MSE, MAE, and MS-SSIM, were compared with a Super-Resolution (SR) CNN, and the PSNR was evaluated. This study concluded that perceptually grounded loss achieves better results. In [11], a systematic review and analysis of various classical and latest image-matching techniques was presented. This study started with feature detection, description, matching, and analysis and provided a proportional study on a handcrafted dataset using a deep neural network. In [12], six classifiers were used, namely, Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree, Random Forest (RF), K-Nearest Neighbor (KNN), and Adaptive Boosting (AdaBoost), to classify neuroimaging data in schizophrenia, autism, ultra-high risk, and first episode psychosis disorders. LR and SVM were the best-performing classifiers.

II. PROPOSED METHOD

This study compares different classifiers on the same dataset. The following steps are used, as shown in Figure 1.

- First, dcm or Dicom images were collected from different open repository databases such as Open Neuro and Kaggle. As all Dicom images had different sizes, all of them were normalized and converted to the same size.
- After normalization, the SSIM was calculated for all images. SSIM was calculated between one and all other images. The dataset includes 342 images, of which 186 are abnormal and 156 are normal.
- After the SSIM calculation, the similarity between the images is marked as 1, otherwise, it is in the range of 0 to 1.
- After calculating the SSIM value for all 342 images, features are extracted using a cross-validation approach and all data are stored in a csv file for training and testing.

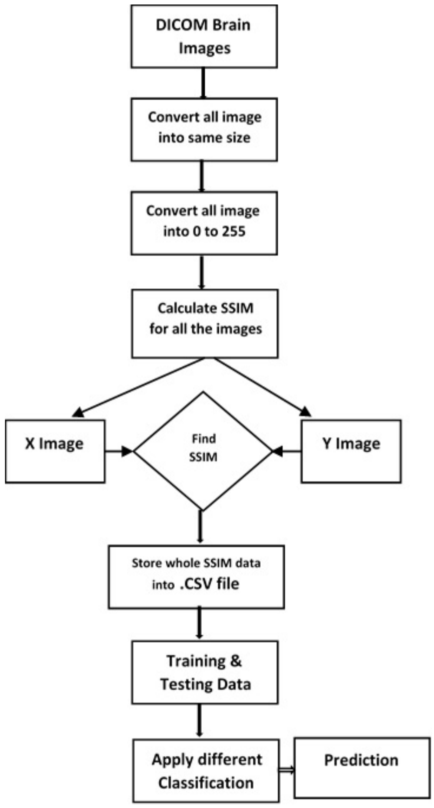


Fig. 1. Proposed model.

A. Dataset

This article uses two types of brain images: normal and abnormal. All brain images were taken from Kaggle [13] and openNeuro [14] open repositories. In [13], some images are normal and some are abnormal having some disease or brain tumors, etc. This dataset contains 253 images, but this study selected images randomly. Similarly, some images were taken from [14]. This repository contains many datasets. All images were acquired by T1-weighted structured Dicom images, captured during a 10-minute resting state. During this period, participants were asked not to think so much and to focus on the purpose of the study. There is a total of 285 scans available, of which images were selected randomly. Using both datasets, a total of 342 images were selected.

Table I shows the details of the Dicom images. All brain images have different sizes, so all images were normalized with padding zeros in rows and columns. After that, all Dicom images have a pixel size of 2^{16}. To normalize the images, they were converted in a range of 0 to 255. After normalizing the images, the SSIM was calculated for all images, comparing each one with all others. In this way, a 342×342 matrix of SSIM values was obtained. All data were stored in a csv file containing 342 rows and 344 columns. The first column contains the name of the image and the last is the level (0 for abnormal and 1 for standard). The level attribute is used for the classification. The dataset was randomly divided into 80:20 for training and testing, respectively. The training dataset includes 132 abnormal images and 109 standard images. The test dataset contains 28 abnormal images and 23 standard images.

TABLE I. DETAILS OF DICOM IMAGES

	Image types	Sizes of MRI images
1	Normal	256×256 , 512×512 , 640×560, 256×248, 384×348, 528×528, 288×262, 144×192, 240×192, 448×359 ,431×357, 469×360, 320x320
2	Abnormal	256×256, 192×192, 64×64

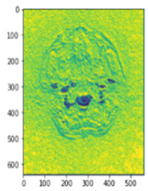
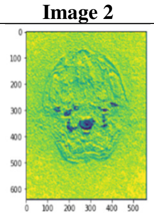
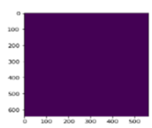
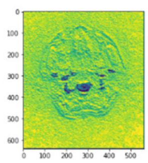
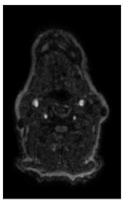
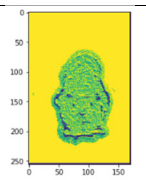
B. SSIM

SSIM is mainly used for image quality checks based on pixels. SSIM is measured between 0 and 1. When comparing two images, a result of 1 means that both images are the same, but a different result means that the images are different or not similar. SSIM is a nonlinear matrix that calculates luminance, contrast, and structure from any image. The following formula combines the luminance comparison function, contrast comparison function, and structure comparison function.

$$I_{SSIM}(x,y) = \frac{(2\mu_x\mu_y+C_1)\,(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)\,(\sigma_x^2+\sigma_y^2+C_2)}$$

where $\mu_x\mu_y$ is for luminance or mean of x and y images, and σ_x is used for standard deviation. C_1 and C_2 are constants. The whole formula is a combination of luminance and standard deviation, i.e., contract and structure. Table II shows some SSIM examples.

TABLE II. SSIM RESULTS

Image types	Image 1	Image 2	SSIM result
Normal vs normal			 1 (same)
Normal vs abnormal			 Normal with Alzheimer: Not similar

C. Classification

1) Support Vector Machine (SVM)

SVM is a supervised discriminative classifier [15]. The primary purpose of using classification on brain images is to identify predefined classes by exploiting techniques for finding dissimilarities. After extracting features from the data, the classification method uses these characteristics to divide the images into classes [16]. SVM aims to flawlessly distinguish data into two groups [17].

2) Artificial Neural Network

ANNs are used in many applications, such as medicine, industry, engineering, etc. [18-20]. An ANN is a closely connected model that is separated into three portions: the input layer, the hidden layer, and the output layer. The input layer receives information. The hidden layer is responsible for extracting patterns and performing calculations to find hidden features in the input [21]. The hidden layer receives input from previous layers, computes the weighted sum, and sends the result to the next layer. The output layer produces the output or results. The activation function decides which neuron is activated.

$$\sum_{i=1}^{n} w_i \, * \, x_i \, + b$$

where w is the weight, X is the input layer, and b is the bias. This study uses a classical or sequential ANN to perform various operations, such as feature extraction and selection. The classifier acts as a binary classifier. The Rectified Linear Unit (ReLU) function is used for the hidden layer, and the softmax activation function is used for the output layer. A traditional backpropagation algorithm trains the ANN.

D. Prediction Architecture for Classification

This study used two types of classification, namely SSIM feature-based classification and image-based classification [22].

1) SSIM Feature-Based Classification

In SSIM feature-based classification, the features are derived from comparing images and calculating SSIM. Here, one image is compared with all other images. Comparing an image with itself provides the result 1, otherwise, it is between [0, 1]. Table III shows 8 features out of 342×342.

TABLE III. SIMILARITY VALUES ON IMAGE COMPARISON

Image	0	1	10	11	12	13	14	15
0	**1.00**	0.71	0.25	0.05	0.05	0.05	0.05	0.05
1	0.71	**1.00**	0.23	0.04	0.04	0.04	0.04	0.04
10	0.25	0.23	**1.00**	0.02	0.02	0.02	0.02	0.02
11	0.05	0.04	0.02	**1.00**	1.00	1.00	0.99	0.99
12	0.05	0.04	0.02	0.99	**1.00**	1.00	0.99	0.99
13	0.05	0.04	0.02	0.99	0.99	**1.00**	0.99	0.99
14	0.05	0.04	0.02	0.99	0.99	0.99	**1.00**	0.99
15	0.05	0.04	0.02	0.99	0.99	0.99	0.99	**1.00**

2) Image Based Classification

In this experiment, features are extracted from the actual images. The neural network is used to classify the image dataset in image-based classification. It fetches all the images as input, extracts features, and classifies them [22].

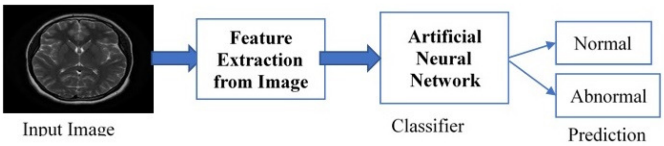


Fig. 2. Classification procedure.

III. RESULTS AND DISCUSSION

A. SSIM Feature-Based Classification

Table IV shows the accuracy of SVM, Naïve Bayes, KNN, and DT with different parameters. Based on the results, SVM with RBF and DT achieved better performance.

TABLE IV. COMPARATIVE STUDY OF CLASSIFIERS

Classification - type	Type	Training/ testing ratio	No. of epoch	Accuracy
SVM – kernel	Linear	80 – 20	500	61%
SVM – kernel	Radial Basis Function (RBF)	80-20	500	100%
SVM – kernel	Sigmoid	80 - 20	500	61%
Naive Bayes	GaussianNB	75-25%	500	67%
Naive Bayes	BernoulliNB	75-25%	500	64%
KNN	-	75-25%	500	96%
Decision Tree	-	75-25%	500	100%

B. Image-Based Classification Result

Neural networks are versatile and persuasive models that work to extract multifaceted patterns in data. Several hyperparameters, namely learning rate, number of layers, batch size, regularization methods, and activation function, influence the behavior of the model, and fine-tuning these hyperparameters can achieve better accuracy [23]. While training the ANN model, the dataset was split into three parts, training (75%), testing (12.5%), and validation (12.5%). The Adaptive moment estimation (Adam) optimizer was used. The batch size was 10, the activation function was softmax, and the learning rate was 0.0001. After training the model with all hyperparameters, an accuracy of 97.7% was achieved along with a training loss of 1.9% in 100 epochs. Table V shows the training accuracy and loss using two optimizers, Adam and SGD, for different dataset training and testing ratios. The loss function is used to train the model. Figure 3 shows that after a few epochs, loss stagnates.

TABLE V. NEURAL NETWORK TRAINING ACCURACY AND LOSS DETAILS

Optimizer	Training/ testing ratio	Epoch no.	Training accuracy	Training loss
Adam	60:40	100, 200	100%	22.4%
Adam	70:30	100	100%	0%
Adam	75:25	100	97.7%	1.9%
SGD	60:40	100, 200	65.2%	68.7%

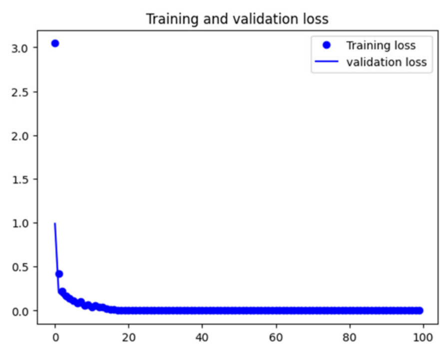


Fig. 3. Training and validation loss.

Figure 4 shows the confusion matrices and Table VI shows the classification report for feature-based and image-based classification. In feature-based classification, only SVM (linear) was considered. The confusion matrix illustrates the model's accomplishment on the test dataset and demonstrates the accuracy of its prediction.

(a)

(b)

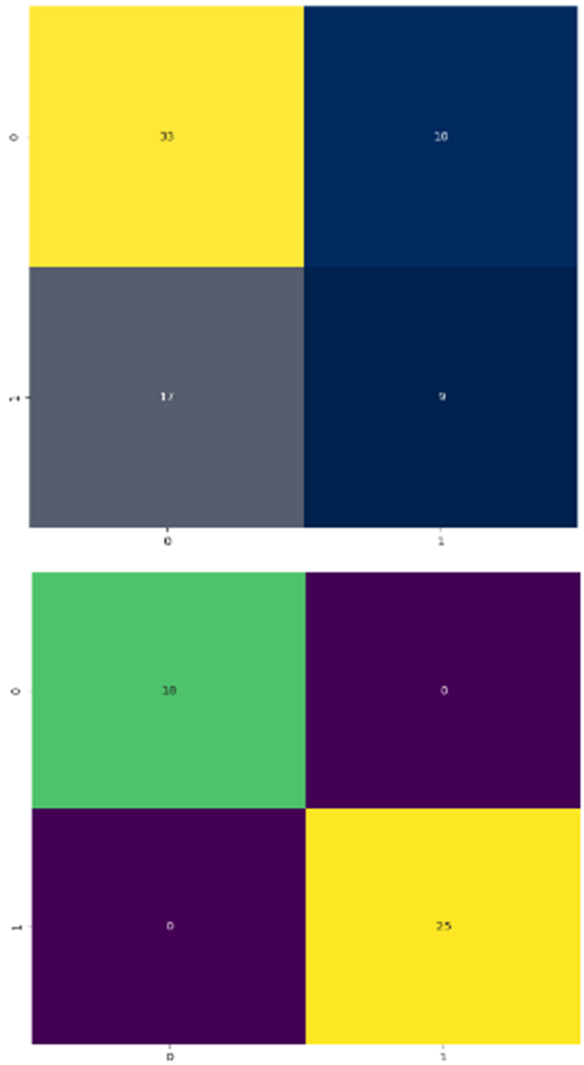


Fig. 4. Classification report for (a) SVM (linear), and (b) ANN.

In SVM classification, the confusion matrix shows that the model predicted that the normal cases were 50 and the abnormal were 17. So the true and false positives were 33 and 17, while the true and false negatives were 10 and 9. Based on the above result, accuracy, precision, recall, and f1-score can be calculated [24-26]. Specificity and sensitivity are described by [27, 28]:

$$\text{Specificity} = \frac{\text{True Negative}}{(\text{True Negative} + \text{False Positive})}$$

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})}$$

For SVM (linear), specificity is 9/(9+10)=0.47 and sensitivity is 33/(37+17)=0.66. Sensitivity shows that 66% of positive data was correctly identified, and 47% of negative or false data was correctly identified. The ANN predicted 18 normal cases and 25 abnormal. So the true and false positives were 18 and 0, while the true and false negatives were 0 and 25. Based on the above result, accuracy, precision, recall, and f1-score can be calculated. For ANN, specificity is 25/(25+0)=1.0 and sensitivity is 18/(0+18)=1.0. Sensitivity shows that 100% of data was correctly identified.

TABLE VI. CONFUSION MATRIX AND CLASSIFICATION REPORT

SVM (linear)					**ANN**				
	Precision	**Recall**	**F1-score**	**Support**		**Precision**	**Recall**	**F1-score**	**Support**
0	0.65	0.79	0.72	43	**0**	1.00	1.00	1.00	18
1	0.47	0.31	0.37	26	**1**	1.00	1.00	1.00	25
Accuracy			**0.61**	**69**	**Accuracy**			**1.00**	**43**
Macro avg	0.56	0.55	0.54	69	**Macro avg**	1.00	1.00	1.00	43
Weighted avg	0.58	0.61	0.59	69	**Weighted avg**	1.00	1.00	1.00	43

IV. CONCLUSION

This study examines image classification using SSIM, which does not require separate feature extraction. SSIM can extract the features using a cross-validation approach. This study used two types of classification: SSIM feature-based and simple image-based classification using an ANN. In the first experiment, 342 images were used to calculate the SSIM using a cross-validation approach, and then a classifier was used. This study used SVM, KNN, Naïve Bayes, and DT for different dataset ratios. In the SVM classifier, linear and sigmoid kernels achieved 61% and RBF achieved 100%. In Naïve Bayes, the GaussionNM kernel achieved 67% and BernoulliNB achieved 64%. KNN achieved 96% accuracy and DT achieved 100%. In the second experiment, 342 DICOM images were used for image-based classification using an ANN. The ANN performance using the Adam optimizer for different dataset ratios was 100% and 97.7%, and using the SGD optimizer was 65.2%. In conclusion, the proposed approach provided the same prediction results. Future studies should involve examining larger datasets with other deep and convolutional neural networks.

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