CLASSIFICATION OF MR IMAGES OF BRAIN USING DENSE NEURAL NETWORK

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Abstract:

In this paper, we develop a customized version of a deep CNN to classify the when identifying MR brain images. Both the computational complexity and the accuracy of the proposed method are assessed. The results of the experiment showed that both the TPP and TPN had significantly increased. As part of the proposed approach, there will be no changes made to the weights in the fully connected layer. The significant reduction in computational complexity has made the technique viable for widespread use. Therefore, the purpose of this paper is to propose an improved alternative to CNN. Compared to the standard CNN approach, the proposed method yields about 3% better outcomes.

Keywords: Deep Convolutional Neural Network, True Positive Rate, True Negative Rate, Image, Classification

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1. Introduction

In the field of medical imaging, deep learning is quickly becoming one of the most prominent applications of artificial intelligence. One pattern recognition area where deep learning techniques are heavily utilized is in the classification of medical images. Applying deep learning-based approaches for categorizing medical images is already standard practice in automated sickness diagnosis systems [1].

One of the primary benefits of DCNN is the remarkable accuracy with which they operate. Such precision is accomplished by using a multi-layer approach in conjunction with an automated feature extraction procedure. However, the remarkable accuracy comes at the cost of a substantial rise in the complexity of the computation. There is general agreement that accuracy is crucial for a system to be helpful in real-time settings. Studies based on DCNN are utilized to classify medical images, according to the reviewed literature [2].

In [1], a method was described for classifying images of brain tumors using deep neural networks. In this study, we use three distinct types of aberrant brain imaging to draw our conclusions. The images are categorized using a conventional training procedure. In [2], it was looked at whether or not DCNN might be used to categorize CT scans of the brain. In this study, we take advantage of the complementing nature of 2D CNN and 3D CNN to increase the effectiveness of the standard approach.

Additionally, in [3], the DCNN is used to make a diagnosis of Alzheimer disease. Pathology diagnosis makes use of DCNN for the classification of positron emission tomography scans of the brain. This work makes use of a two-tiered categorization strategy.

In this paper [4], the authors offer a deep learning method for image classification that is grounded in human visual perception. In this paper, we investigate problems caused by the standard approach and suggest ways to fix them. In [5], the idea of employing deep autoencoder neural networks for the categorization of f-MRI brain images is introduced. An exact diagnosis of schizophrenia can be made using this procedure. For a more in-depth analysis of deep learning applications in the medical field [6].

The article delves into the different applications of DNN and DCNNs in medical imaging. Additional to that, this work dissects and discusses a wide range of deep learning architectures. A customized deep neural network is used for pattern recognition [7]. As a result of the changes, fewer training images will be needed in the long run. There is no finite limit to the potential uses for this method. Creating a medical image categorization system using Deep Residual Networks is described in depth in reference [8].

We employ four separate kinds of abnormal categories here. Nonetheless, the complexity is very high due to the extensive use of layers. In [9], the authors explore the possibility of employing deep neural networks to categorize cases of autism. For this study, we simply used a binary classification scheme (normal/abnormal). However, each stage of autism must be examined separately if its development is to be comprehended in its whole.

The proposed approach has been modified so that it can be trained with a smaller data set. In order to evaluate the efficacy of this method, we will concentrate on how well it works when classifying data. A DCNN is presented to classify medical images with several modalities. Much like the proposed method, this one emphasizes precision. The application of a deep convolutional neural network for glioma tumor classification and subclassification is demonstrated in [10]. The improvements in the field of computation [16] and network [17] bandwidth is highly important for innovation in this field.

In this study, we evaluated the efficacy of our methods by looking at how sensitive and specific they were. Seizure detection and diagnosis are two other applications where deep convolutional neural networks have proven useful. There is a lack of citations for this section. Another paper that investigates the potential of deep convolutional neural networks in the diagnosis of brain cancer is. Furthermore, DCNNs are used to categorize numerous forms of medical images.

Pathology detection in brain images is the focus of this study, which proposes using a trained DCNN with several modifications. Traditional DCNNs make the adjustment to the layer that stores all of the connections. Assigning weights to nodes in a standard DCNN model fully connected layer is employed instead of the more standard gradient descent training procedure.

2. Background

McCulloch and Pitts did not describe the artificial neuron for the first time until 1943 [11]. This has grown from symbolic, rule-based AI paradigms to hand-crafted algorithms for identifying and classifying characteristics to modern multi-layered or deep neural networks. Currently, this is the most advanced form of AI.

Fukushima Neocognitron model from 1982 [12] inspired the first CNN, which went on to get significant attention thanks to the efforts of researchers. Since CNNs can automatically learn high-level visual qualities and extract features from images, they have become the most preferred architecture for machine learning in image recognition applications.

The field of machine vision has found many applications for CNNs, including picture classification, object recognition, and phrase semantic segmentation. CNNs have shown performance that is on par with or even better than that of human doctors when it comes to the categorization and diagnosis of two-dimensional medical images.

Analyzing volumetric MRI or CT data has been attempted with a variety of machine learning techniques, including two-dimensional CNN. These projects required extensive manual preprocessing, feature generation and segmentation by hand, as well as slice choosing by hand, before classification could even begin. This entire process was performed manually. Several of these techniques streamline the process of categorizing 3D data by focusing on individual images within a volumetric image stack. Some writers have even tried using 2D CNN to all three dimensions simultaneously. The axial, coronal, and sagittal planes are the names given to these axes [13].

By first resampling a 3D volume of interest into 2D images are used to train their CNN on augmented versions of these 2D views, which they then used to detect abnormal lymph nodes in thoracic CT scans. In doing so, they were able to pinpoint lymph nodes that were functioning abnormally. Although its CNN generated an average of six false positives for each patient, it nevertheless managed a sensitivity of 90%. Because of the time and effort involved in hand-crafting, feature segmentation, and stripping, as well as the possible loss of spatial contextual information that might occur when evaluating a 3D volume using 2D slices, traditional approaches can be wasteful. Fortunately, these issues can be resolved.

Dou et al. [14] analyzed MRI brain scans for signs of cerebral microbleeds using a two-stage, three-dimensional convolutional neural network (CNN) that screened for microbleeds and then detected them. The method they used was 93% sensitive but 44% accurate and resulted in an average of 2.7 false positives per patient.

The three-dimensional convolutional neural network (CNN) is a relatively new design that has proven to be most effective when applied to the processing of moving images and three-dimensional volumetric medical images. High computational cost and extended processing time required to handle 3D kernels and whole volumes of pictures historically hampered the deployment of 3D CNN. However, there has been a rise in the amount of 3D CNN-related studies appearing in academic journals. The decline in the cost of computing hardware definitely boosted the popularity of these investigations. CNNs, or 3D convolutional neural networks, have been used in the medical imaging area for anomaly identification in CT and MRI scans of the liver, lungs, heart, and brain. Another indicator that this clinical issue is gaining greater focus is the growing body of literature on automatic intracerebral hemorrhage identification on MRI and CT scans utilizing 3D convolutional neural networks [15].

3. Proposed Method

In this section, we present the two different feature extraction models and then the classification is conducted on features using CNN.

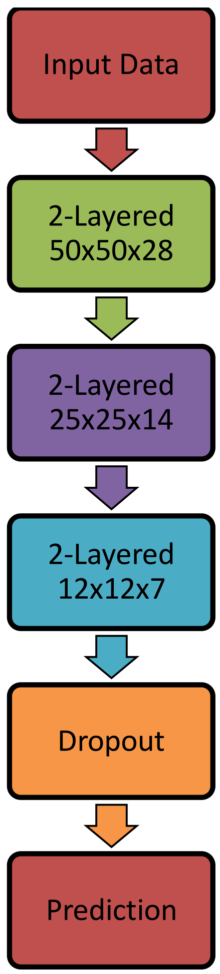

Figure 1: CNN Classification

Geometric features

The given procedure involves removing geometric features, also known as form features, from the entire dataset. In this research, we will use the retrieved geometric features to quantify the unique geometric aspects of the tumor area. Thus, there are nine geometric properties that can be inferred from any given shape. Area, major axis length, filled area, orientation, extension, perimeter, solidity, and circularity are some of these characteristics. After these features have been calculated for the segmented tumor region in each image, the resulting matrices are concatenated to produce R. After retrieval, the geometric attributes and image labels are stored in the matrix R. In the following step, called feature fusion, the calculated matrix R is employed. The primary objective of feature extractions is to obtain geometric information about tumors and combine it with information about how they feel to improve the accuracy of the classification process.

Counting the number of ON pixels in an image is how the filled area, denoted by A in the equation, is determined once all holes in the image have been filled. For typical images, the sum of all the ones should equal 0. This is because the filled region is indicated by the sum of all the ones. Integers lower than Area will be generated by this function.

The study may get a sense of the orientation of a segmented image by calculating the angle between the horizontal axis and the main axis. The symbol represents this particular angular degree. Once this single scalar value has been analyzed and returned as a scalar, it can be incorporated into a feature vector. The perimeter of a binary image can be calculated by summing the values of the bordering pixels. If you want to know how solid an image is, just divide its entire area by the area of its convex parts.

In geometry, the major axis length of an ellipse is the furthest distance between any two points on the ellipse surface and its foci. The diameter of an ellipse is greatest at its furthest distant point from its center. The shortest distance between any two points on the ellipse surface and its foci is its minor axis. The diameter of an ellipse is the measure of its smallest length, or the distance between its two ends. Scalar circularity is calculated by multiplying a constant by the result of area divided by square of perimeter. Next, another constant value is multiplied by this one.

Texture features

Evaluating an image texture has been given a lot of attention in computer vision, and texture features have played a big role in this. In medical imaging, texture features are used for pathology evaluations including those of tumors and lesions. This is feasible because the texture of every tumor may be statistically represented separately. Because of this, a direct comparison between the two is impossible.

When it comes to texture classification, what required is the extraction of features. This data is created from grayscale images and reveals geographical information as well as intensity fluctuation. They are generated and categorized as texture features for the purpose of extracting texture information from an image. One strategy for enhancing classification precision is to compute texture characteristics. The texture features can be determined in two ways: systematically and statistically.

The texture contrast, correlation, uniformity, and homogeneity are the four features that are drawn out. With the goal of ensuring that only high-quality data is used, it was determined that just four features would be considered. Contrast is a characteristic of images that, when queried, returns the absolute value of the intensity difference between a given pixel and its neighboring pixel throughout the entire image. Then, a feature vector is built to characterize this distinction. If the two images have absolutely no differences, the contrast value will be 0.

The correlation image property returns a number between -1 and 1, or NaN if there isn't enough information to determine a meaningful value, to describe the degree to which a pixel is related to the pixels surrounding it. The homogeneity attribute of a image is the sum of the squares of the GLCM elements and can take on the values 0 and 1. The homogeneity of a image is a quality that quantifies how similarly spaced the texture individual pieces are. It is also called the inverse difference moment and has a value of 1 for the diagonal GLCM. The inverse difference moment is one way to quantify homogeneity.

Means, standard deviations, skewness, and kurtosis are calculated for the texture features after they have been retrieved. With the GLCM technique, we look into the connections between matrices that are side-by-side on the horizontal. After performing a binary segmentation, the GLCM features skewness and kurtosis are computed by examining the pairs of horizontally adjacent matrices of size 2 x 2 = 4 and a final vector of size 1.

$$\text{Kurtosis } KR=E[((x_i-\mu)/\sigma)^4]$$

Using a basic concatenation technique based on the idea of serialization, we are able to combine geometric and textural features. When two sets of features are combined into a single vector, the fusion process is able to generate more reliable results. All these feature collections tell us something unique about the patterns they represent.

$$S=\frac{E\left(x_i^3\right)-\mu^3-3\mu\sigma^2}{\sigma^3}$$

Specifically, a GLCM technique developed in the past is employed for feature selection with a mean squared error cost function to get the desired results. To classify data using CNN, one must first extract the most relevant features that have been manually selected.

CNN classification

CNNs are a subset of neural networks that, like deep neural networks (DNNs), are optimized for visual analysis. Nonetheless, a CNN is purpose-built for the purpose of conducting image analysis, while a DNN can be used for a variety of tasks. As a result, the neural network can be trained to better perform image-centric tasks by incorporating image-specific information into its architecture. As a result of its straightforward yet precise design, a CNN can effectively translate massive amounts of visual input into actionable insights.

Earlier attempts to use neural networks or multi-layer perceptron models for image recognition relied on these methodologies. However, the full connectivity between nodes led to the curse of dimensionality, but a CNN weight sharing structure and pooling algorithms enabled it to drastically reduce the number of parameters, making it a more effective tool than DNNs for evaluating imaginative images. Keep in mind that CNN does not encode the location or orientation of the objects it detects because it is spatially invariant. This limited CNN usefulness in applications were knowing where data is located was crucial. There are many applications for CNNs in the field of architectural design research, including generative design and classification.

Adding more layers did not significantly reduce the loss while significantly impacting the processing time. The proposed CNN model makes use of 32 convolutional layers. Similarly, increasing the CNN layer count did not significantly enhance CNN loss accuracy.

4. Results and Discussions

A PC with a 2.50 GHz processor and 16 GB of random-access memory is used in the classroom and for tests (RAM). The Keras library, which provides a Python-based interface for Deep Learning, is used to build the models. We use MSE as the loss function over MAE since it is more sensitive to huge errors. To ensure the model predictions are as accurate as possible, this is done. The Adam optimizer was selected for this project because of its proven track record in model optimization. We use datasets of varied sizes to train the two models. There were 350 samples utilized in the first experiment and 1050 samples used in the second. A random 80:20 split is used to divide the datasets into the train set and the test set.

Because it can cause serious complications or even death, acute brain bleeding is a frequent reason for neurosurgical emergencies. Several things, including a trauma to the head, high blood pressure, or a ruptured brain aneurysm, can lead to this condition. The best course of action in dealing with this illness is contingent on pinpointing its precise cause. Whether the patient needs emergency neurosurgical intervention or can be continuously followed in a facility with a focus on intensive care or high dependency depends on their present clinical condition. An individual has a better chance of reaching a full recovery if the delay between diagnosis and treatment is minimized.

We suggest using an automated 3D convolutional neural network to categorize volumetric CT brain data into several types of hemorrhage. It will let doctors determine what wrong with patients and start treatment immediately. In order to correctly classify CT brain scans into normal, SAH, IPH, ASDH, and BPH categories, we trained and tested on 399 images of CT brains taken in our hospital. The selection of these groups was prompted by the fact that they get various levels of neurosurgical care.

We also conceived and implemented an original pixel thresholding technique for identifying recent bleeding in CT brain imaging. The strategy described here was put into action. This approach was useful for our dataset, and it has the potential to be extended to other datasets for use in identifying acute bleeding in different anatomical locations. This method has the potential to aid in the diagnosis of other diseases, including malignancies, in addition to acute blood problems.

Unsupervised learning approaches for 3D object synthesis are emerging as CNNs and 3D CNNs have dominated image analysis. The analysis of three-dimensional medical images has been the primary focus of the research into these techniques. There has been no effort to use generative designs like variational autoencoders and generative adversarial networks to volumetric medical data, despite the fact that these methods may lessen the demand for big, well-labeled datasets. Despite the usefulness of such an application, it cannot be implemented at this time.

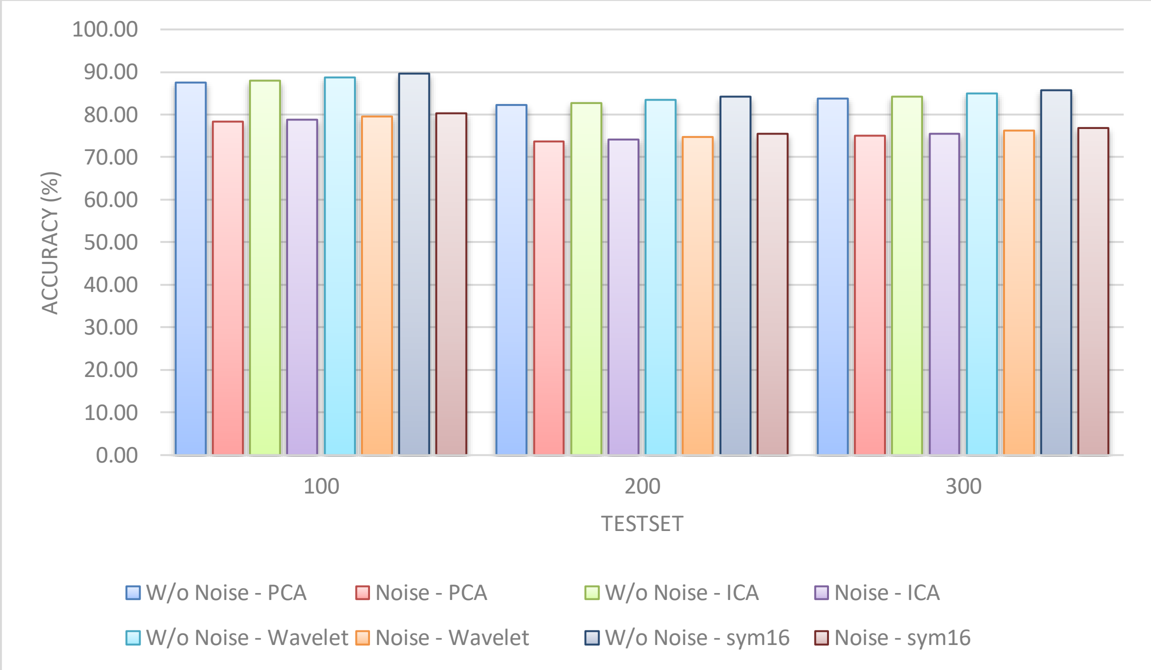

Figure 2: Accuracy of Training

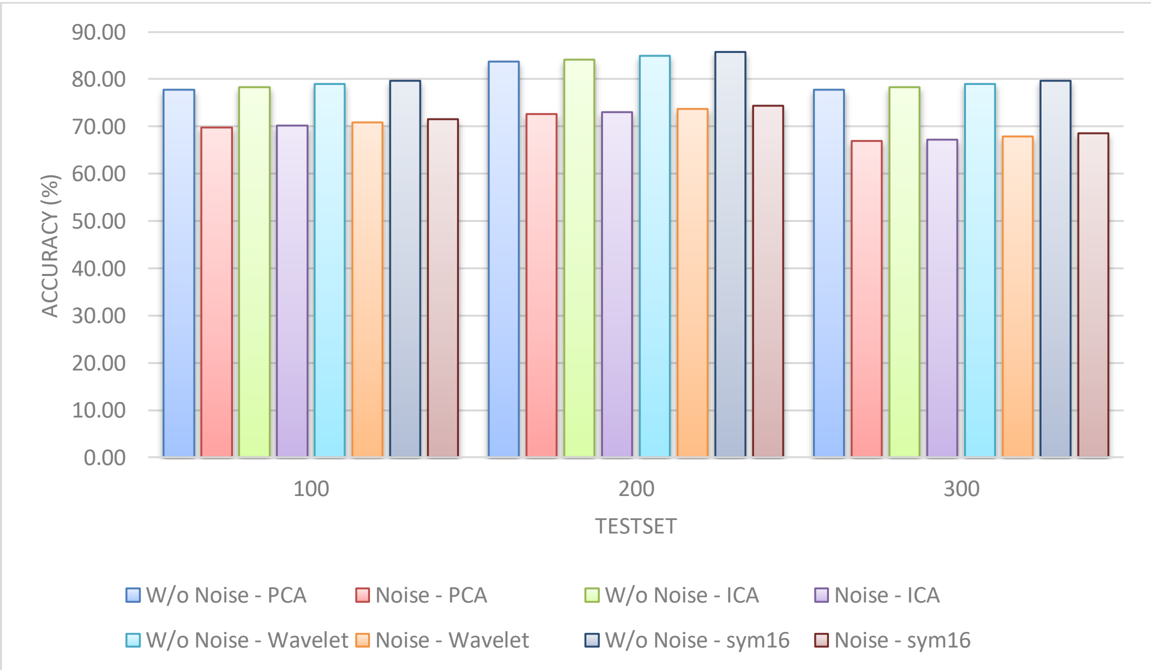

Figure 3: Accuracy on Testing

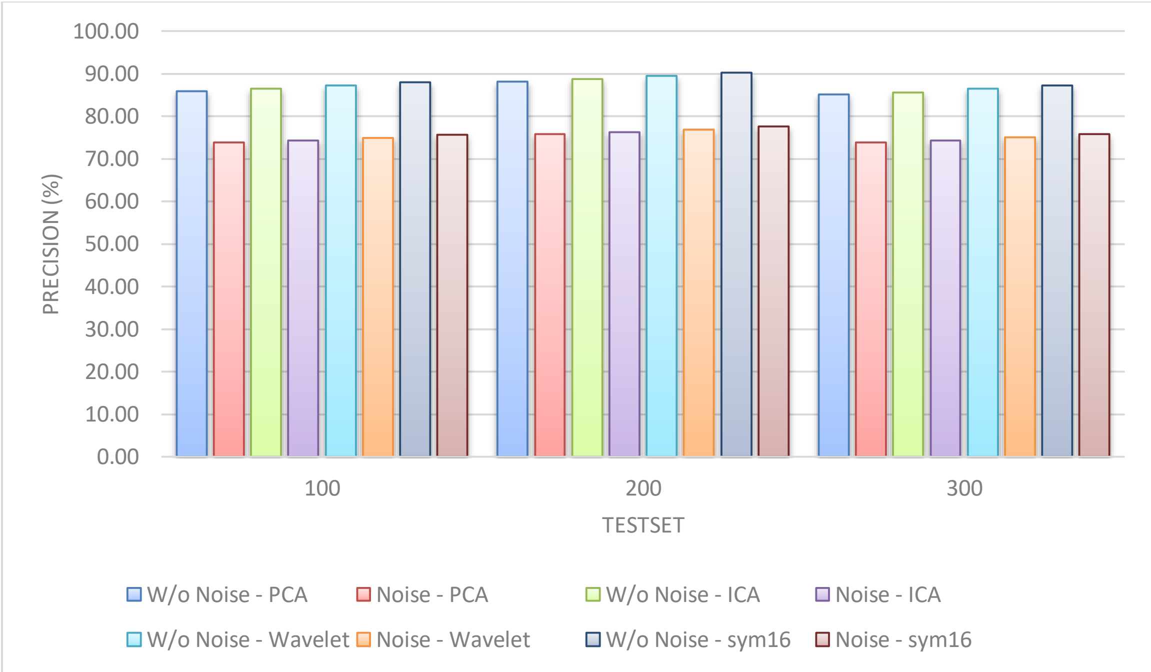

Figure 2: Precision of Training

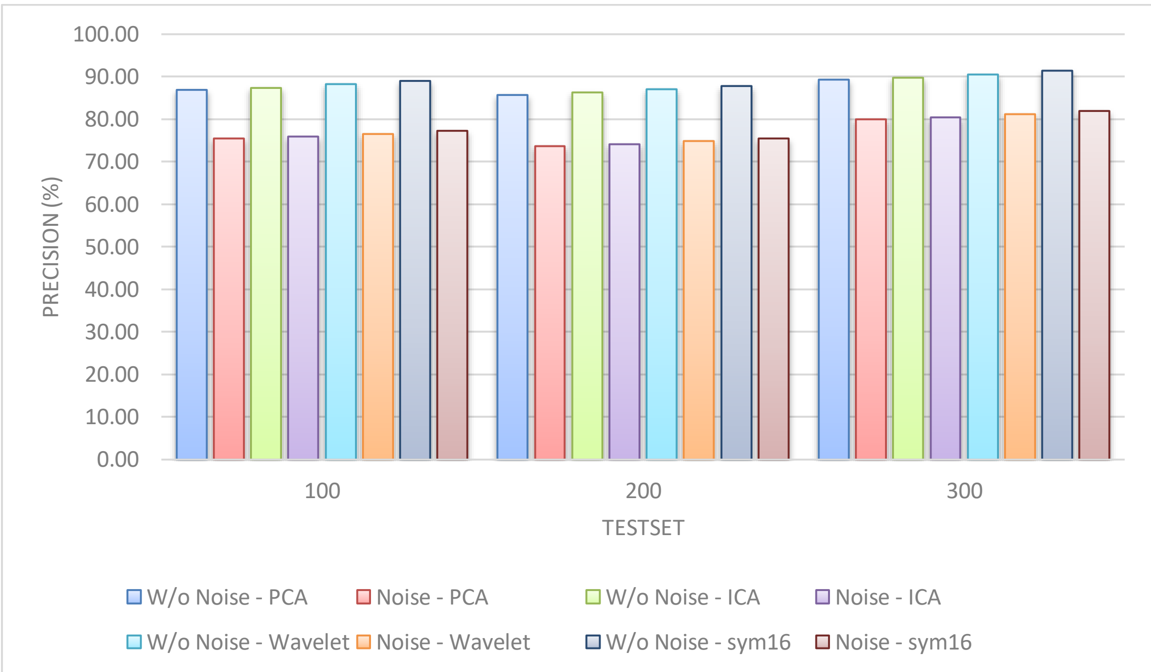

Figure 3: Precision on Testing

This means that the proposed method is preferable to the standard one since it requires less computational complexity. Testing was done using real-world images, hence there is no cross-reference analysis here. The importance of using the same dataset and configuration variables when comparing your work performance to that of other published studies cannot be overstated. However, when we look at all of the studies that have been done on the topic, we find that algorithms based on CNNs are very accurate in classifying medical images. As compared to state-of-the-art CNN-based image classification methods, the suggested methodology significantly outperforms the competition.

5. Conclusions

This research suggests utilizing a customized version of a deep convolutional neural network when identifying MR brain images. Both the computational complexity and the accuracy of the proposed method are assessed. Compared to the standard CNN approach, the proposed method yields about 3% better outcomes. The results of the experiment showed that both the True Positive Rate and the True Negative Rate had significantly increased. As part of the proposed approach, there will be no changes made to the weights in the fully connected layer. The significant reduction in computational complexity has made the technique viable for widespread use. Therefore, the purpose of this paper is to propose an improved alternative to CNN.

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