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ANN Algorithm for Brain Hemorrhage Detection Using CT Images

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Abstract. Brain hemorrhage is a type of bleeding that might occur in more than one location in the brain. It is usually imaged by Computed Tomography (CT). These images of hemorrhage allow accurate disease prediction and efficient patient assessment of morphological changes in the brain as the recovery progresses. CT image processing is commonly used to enhance the visual details on an image. This study examines the ability of Artificial Neural Network (ANNs) classifier to detect the existence of brain hemorrhage based on CT images. The proposed algorithm was tested on 200 brain CT images; the dataset contained 100 normal and 100 abnormal cases. The results indicate a sensitivity of 79.8%, a specificity of 82.3%, and a classification accuracy of 81.0%. This algorithm can be used as a guiding tool for trainee radiologists to test expert diagnosis and to minimize mistakes in the current techniques. In conclusion, the classifier is useful to classify the images, and helps to diagnose the disease automatically without manual guidance by the users.

Keywords: Brain haemorrhage, ANN, CT, image processing.

1. Introduction

Brain hemorrhage is a type of disease that occurs in the brain and is known as "cerebral hemorrhage", it occurs due to an artery that bursts in the brain and makes locally bleeding tissue. It was classified as a third cause of death after heart and cancer disease[1]. Symptoms of brain hemorrhage may differ based on bleeding situation, area of tissue influenced, and the seriousness of the bleeding.

Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are two types of imaging that can be used to diagnose. CT images have several benefits over MRI due to its low cost, wider availability, faster technology, and usefulness if the patient has metallic implants[2]. In this study, we will be using CT images of brain hemorrhage to build an algorithm, based on image processing and Artificial Neural Network (ANNs), to automatically detect brain hemorrhage.

2. Related Work

Many studies presented different algorithms to automatically detect brain hemorrhage. The paper by Myat Mon Kyaw has presented a simple automated technique for detecting and classifying an abnormality (hemorrhage) in brain CT images. In his paper, the author preprocessed the image to remove the skull, then images were divided into four regions in order to detect the area of bleeding[3]. Paper by Gong et al. described a technique of automatically classifying CT brain images of various types of head trauma. The proposed approach was combining three steps : segmenting potential anomalies relative to the predefined criteria, by grouping homogeneous areas, then features like area, main axis length, etc., are extracted for each region and each feature extracted is classified by means of an automated learning algorithm[4].

The prospect of identifying brain bleeding was examined in a study by [5] by image segmenting CT scan pictures using the watershed approach and feeding the necessary inputs taken from the brain CT image to an artificial neural network for classification. The automatic detection of bleeding was found by the authors to be a very challenging challenge; after applying the watershed technique, the boundaries of each zone were continuous and over-segmentation issues appeared. This procedure took a little bit of time. However, during the testing phase, the accuracy was 80%,

R. Ganesan and S. Radhakrishnan have used segmentation of the CT brain images via Genetic Algorithm assessed by receiving operating characteristics (ROC) curve analysis[6]. Liu et al. have shown an automated

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CT scan slice detection with bleeding. There are two parts of the detection method. The first part divides the scan sections into the area of the encephalic and nasal cavity. The second part detects abnormal slices in the encephalic region, the Wavelet and Haralick texture models were used in both parts [7] . Another study, they suggested a Fuzzy C-Means alternative (FCM) method for segmentation[8].

Convolutional neural networks with deep supervision (CNN-DS) were provided by Arab et al., and they were successful in achieving an F1- score of 0.84 and a sensitivity of 0.83[9].

Grewal et. al. presented 3D CT scan model by merging the Convolutional Neural Network (CNN) network with the Long-Short Term Memory (LSTM) network for 329 brain CT images. They improved their hemorrhage prediction accuracy by 81.82% when compared to three radiologists, and their strategy outperformed two radiologists [10]. In addition to detection, Hssayeni et al. sought to segment cerebral bleeding; they achieved 97.2% sensitivity and 50.4% specificity [11].

In order to diagnose the brain hemorrhage along with the geometrical and textural feature, Shelke et al. uses image processing techniques and medical filters, as input into the neural network machine [12]. AH Ali et al. suggested that the bloody strokes can be detected and segmented using texture analyzes from brain CT images, the threshold segmentation process is utilized in the study to obtain the area of the stroke from the CT brain image and a first-order histogram was calculated the statistical feature, as a result, the white color of the image was the mean value, the relatively high mean shows an abnormal region of the brain [13]. M Chawla et al. have introduced an automated method for the identification and classification of an abnormality into acute and chronic CT disease and hemorrhage at a non-contrast CT slice level[14]. Jnawali, et al. proposed 3D CNN architectures to predict brain hemorrhage; they begin by extracting characteristics from CT images. Following that, they employed a logistic function to predict brain bleeding. Whereby the dataset contains 40,357 CT brain images, 30,001 of which indicate no hemorrhage and 10,356 of which suggest hemorrhage. To reduce the data unbalance. They achieved 77% sensitivity and 78% F1 score[15].

The accuracy of the methods discussed studies above is highly sensitive to noise. Therefore, in this study we aim to propose a new algorithm to detect brain hemorrhage with lower sensitivity to noise and acceptable accuracy.

3. Methodology

Our proposed algorithm includes 3 main stages: 1) image pre-processing stage to reduce the noise and improve the quality of images 2) extraction and selection the features to enhance the accuracy of classification 3) Artificial Neural Network to classify the images in two classes; hemorrhage free brain, and a brain with hemorrhage. The proposed method flow chart is shown in (Figure 1); each step will be discussed in detail in the following sub-sections.

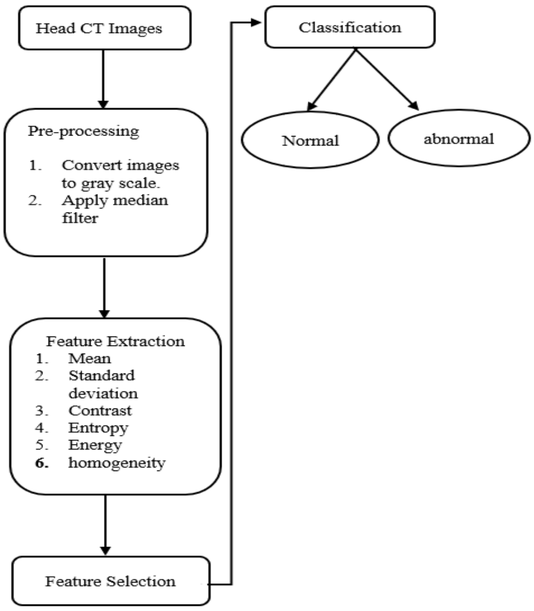


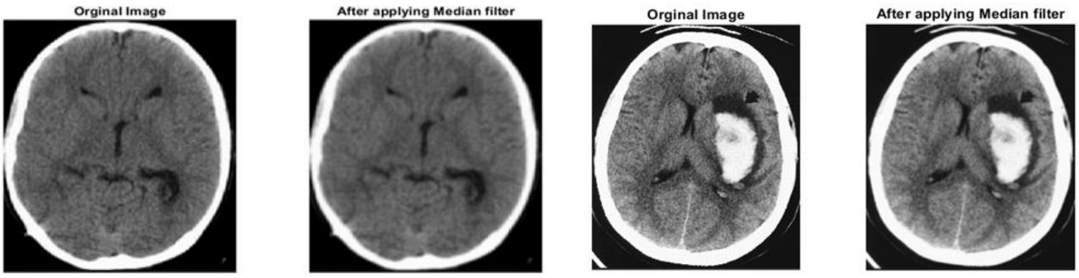
Fig. 1: Flow chart of proposed method.

3.1. Data Set

The dataset for human brain hemorrhage from Kaggle1 is used, which included 200 CT images for human brain ,the images were divided evenly, 100 normal images and 100 abnormal images. There is no differentiation between the type of hemorrhages, and each slice is taken from an individual. The goal of this dataset is to uncover strategies to anticipate imaging findings with limited data. CT images assist to simultaneously recognize the bone, soft tissues, and blood vessels.

3.2. Preprocessing

This stage was applied to reduce the noise of brain tissue. The stage is divided into two steps; Converting images to grayscale to facilitate application of median filter step. Median filtering in digital image processing is very common because it maintains edges during noise removal. Figure 2 below showed two examples of the used images before and after applying the maiden filter.



a. b. c. d.

Fig. 2: a. Normal head CT before applying median filter. b. Normal head CT after applying median filter. c. Haemorrhage head CT before applying median filter. d. Haemorrhage head CT after applying median filter.

3.3. Features Extraction

Extraction of the feature is the most important step in designing this system. It should be able to extract useful and distinctive features from images; these features are inputs to ANNs classifier. The main goal of this extraction, by measuring specific features, is to minimize the input size of our datasets. Some features need GLCM (Grey Level Co-occurrence Matrix), the mechanisms of GLCM are characterizing the texture of an image by calculating how often pixel pairs with certain values occur in an image and in a certain spatial relation. In this proposed methodology the features chosen were based on feature used in previous studies:

- Mean[16]:
- Standard deviation [16]
- Contrast: measure the contrast of intensity between each pixels and neighbour pixels about the entire image [17]: $$contrast = \sum_{i,j} (\mathrm{i}-\mathrm{j})^2\, \mathrm{p}(\mathrm{i},\mathrm{j}) \tag{1}$$
- Correlation: measure how the pixel correlated with neighbour pixel about the entire image [19]: $$correlation = \sum_{i,j} \frac{(i-\mu_i)(i-\pi_i)p(i,j)}{\sigma_i \sigma_j} \tag{2}$$

$where \quad \mu_i = \sum_i i \sum_j p(i,j) \quad , \mu_j = \sum_j j \sum_i p(i,j),\ \sigma_j = \sum_j (j-\mu_j)^2 \sum_i p(i,j) \quad , \sigma_j = \sum_j (j-\mu_j)^2 \sum_i p(i,j)$

- Energy: the sum of squared elements in the GLCM [5]: $energy = \sum_{i,j} p(i,j)^2$ (3)
- Homogeneity: a value that evaluates proximity in the GLCM matrix to the GLCM diagonal for the element distribution [18]: $homogeneity = \sum_{i,j} \frac{p(i,j)}{i=(i-j)}$ (4)

Where p(i, j) is the signal intensity of the pixel located for row i and column j, we apply for all i and j.

3.4. Feature selection and Classification

Artificial Neural Network (ANN) is a computational system that takes its concept, structure, and function from the human nervous system. ANN led to many applications such machine learning and pattern recognition. ANNs has two modes: 1) training mode 2) testing mode. The information transmitted in one directional pathway beginning from input layer, to hidden layer and finally, to output layer [16].

[1] https://www.kaggle.com/datasets/felipekitamura/head-ct-hemorrhage?select=head_ct

The multi-layer perceptron (MLP) is an ANN model that belongs to the feedforward network class. In 1958, Frank Rosenblatt created the perceptron technique at the Cornell Aeronautical Laboratory. It is a supervised learning model that produces a set of outputs from a variety of inputs; it trains the network through backpropagation. This backpropagation approach aids in calculating the gradient of a loss function across all network weights. It has many applications, especially in segmentation and pattern recognition. In this system, the 200 images are divided with two different ratios; first division was 70%, 15% and 15%; second division was 80%, 10%, and 10% for training, validation and testing respectively. Testing is performed to assess the system performance without any effects on training (i.e., the network performance during and after training is measured independently). This classifier was built in this study via MATLAB software.

In contrast to traditional networks, which used to contain a single hidden layer and were known as shallow networks, deep learning illustrates neural network topologies with multiple hidden layers[19].

The two different ratio groups were tested with different number of hidden neurons: 10, 15, 20 and 25 hidden neurons. The input was transmitted from the input layer to output layer by hidden layer. The input of this network represented the features extracted from the images. The images are then classified according to the value of these features into two classes, either normal or abnormal images. See Figure 3. The above-mentioned steps have been applied via MATLAB.

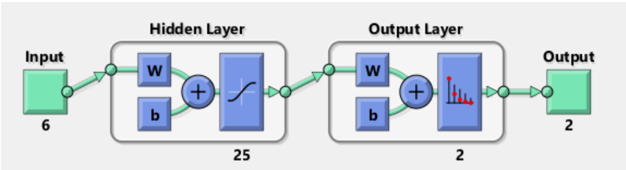


Fig. 3: Block diagram of Neural Network.

4. Experimental Result and Discussion

This section discusses the experiments carried out to evaluate the quality of the results produced by the proposed method.

4.1. Performance Metrics

Result assessment can be done by comparing the results from senior radiologist diagnoses to that result from the proposed algorithm. This assessment includes the calculation of TP, TN, FP, and FN which represent the True Positive, True Negative, False Positive, and False Negative respectively. From these values we can calculate sensitivity, specificity, and accuracy according to the following equations.

$$SENSITIVITY = \frac{TP}{TP+FN} \times 100 \tag{5}$$

$$SPECIFICITY = \frac{TN}{TN+FP} \times 100 \tag{6}$$

$$ACCURACY = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{7}$$

4.2. Classification Results

In this study, 79 images out of 100 (abnormal) and 83 images out of 100 (Normal) were diagnosed via ANN correctly. On the other hand, 17 images out of 100 (normal) and 21 images out of 100 (abnormal) were diagnosed via ANN wrongly. Therefore, according to the equations (5) and (6) above; system sensitivity and specificity, when using 25 hidden layers, were 79.8% and 82% respectively. Sensitivity indicates the people with brain haemorrhage were correctly identified by ANN, and the specificity indicates the people without brain haemorrhage were correctly identified by ANN, see Figure 4.

The classification accuracy of two different ratio groups when trying different number of hidden layers is shown in Table 1. From table 1, we noticed that when increasing the number of hidden layers in group 1 the accuracy increased and reach the high value among of them whereas in group 2 when increased the number of hidden layers the behaviour of this system does not clear and the highest value in this group when the hidden layer was 15.

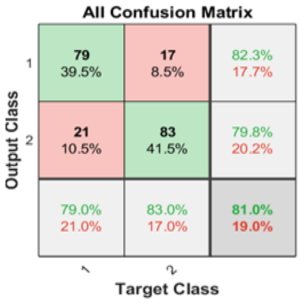


Fig. 4: confusion matrix of the ANN classifier when using 25 hidden layers.

Table 1: Comparison between numbers of samples with different number of hidden layers.

No of Sample	Hidden layer	Accuracy %
Group 1	10	75.0%
	15	76.5%
	20	77.0%
	25	81.0%
Group 2	10	74.0%
	15	80.5%
	20	79.5%
	25	79.0%

The Suryawanshi et al. [20] utilized the watershed approach which was more time-consuming and there were some difficulties with the segmentation phases when we compared the overall results to ours. Our investigation yielded a higher accuracy in less time and with a simpler approach. Comparing the (ANN-MLP) against 3D-CNN[9] and the hybrid model (CNN-LSTM)[10], we observe that these two studies used a complex approach and obtained a slightly higher accuracy than ours. Nevertheless, we were able to achieve a result like their approach with a simple approach and by using only one filter to remove noise. Hssayeni et al. sought to segment cerebral bleeding; they achieved 97.2% sensitivity (true positive rate)and 50.4% specificity (true negative rate) [11] which is mean the model has a precision of 50.4%, when it predicts a no brain haemorrhage, it is correct 50.4% of the time, and it correctly identifies 97.2% of all haemorrhage. The model may be overfitting and have low precision and high false positive (FP) rates, which indicate that the model is committing numerous errors and it did not perform well on unknown data.

In contrast to the prior study's [15] large dataset , we propose a less complex methodology with a small dataset that also requires less time to train models. The second goal is to prevent every single life lost due to faulty diagnosis and doctor negligence, which necessitates improved prediction outcomes, therefore our research yielded better results than this study. We run our experiment on a PC with 1.80 GHz Pentium i5 CPU using MATLAB. The average runtime per image of the pre-processing part is 7.1 second. The average runtime of the ANN part is 1.35 minutes. By overcoming difficulties such as overfitting, underfitting, complexity, accuracy, time consumption, accuracy, and model depth, we attempted to produce the highest and most accurate prediction outcomes in this study.

5. Conclusion and Future Work

This paper presented an algorithm for brain haemorrhage detection using ANN with acceptable accuracy reaching 81%. This system is expected to help diagnose the disease automatically using personal computers and without making hard effort by the users, or even much of experience. However, increasing the used dataset size is required to enhance the system accuracy and hence its efficiency. Various brain haemorrhage detection methodologies required high segmentation, noise reduction, accuracy, and so on; in this study, these challenges were overcome by employing an advanced neural network in terms of accuracy, speed, and robustness.

For the future work, we can use another classifier such as K-mean clustering, Support Vector Machine (SVM), K-Nearest Neighbours (KNN) classifiers, or Fuzzy mean and make a comparison between any of these classifiers and ANNs to gain a higher accuracy. In addition, utilizing more features to improve the performance of system, however, this will need a more powerful PC.

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