Classification of intracranial hemorrhage (CT) images using CNN-LSTM method and image-based GLCM features

Swetha Mucha 1* and A. Ramesh Babu 1

1 Department of Computer Science and Artificial Intelligence, SR University Warangal - 506371, Telangana, India.

Abstract. A hybrid feature-based method is used, combining transformed-based features with image-based grey level co-occurrence matrix features. When it comes to classifying cerebral hemorrhages CT images, the combined feature-based strategy performs better than the image-feature-based and transformed feature-based techniques. Natural language processing using deep learning techniques, particularly long short-term memory (LSTM), has become the go-to choice in applications like sentiment analysis and text analysis. This work presents a completely automated deep learning system for the purpose of classifying radiological data in order to diagnose intracranial hemorrhage (ICH). Long short-term memory (LSTM) units, a logistic function, and 1D convolution neural networks (CNN) make up the suggested automated deep learning architecture. These components were all trained and evaluated using a large dataset of 12,852 head computed tomography (CT) radiological reports.

1 Introduction

For patients, a brain haemorrhage is a life-changing event. Accurate diagnosis is critical in the medical industry because it allows doctors to treat patients more quickly. Intracranial haemorrhage (ICH) is a complex condition. Intracerebral haemorrhage and subarachnoid haemorrhage are two types of intracerebral haemorrhage. Intracerebral haemorrhage occurs when blood vessels in the brain tissue bleed. Subarachnoid haemorrhage, on the other hand, is caused by bleeding in the brain's surrounding space. The majority of the time, an ICH diagnosis entails a physical examination and a review of the patient's medical history. Because 50 percent of patients die within 24 hours, accurate and timely diagnosis is critical. Within a month, 35 to 52 percent of patients enter the critical zone and die, with mortality reaching 60 percent after 30 days. A clinician uses non-contrast computed tomography (CT) analysis to do a first stage examination in order to make an accurate diagnosis. CT image analysis aids in identifying and locating the source of the bleeding inside the brain.

* Corresponding Author : ramdasv786sap@gmail.com

© The Authors, published by EDP Sciences. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).
In an effort to speed up diagnosis and enhance clinical workflow, the majority of research in recent years has concentrated on the categorization, identification, and detection of cerebral hemorrhage. Specifically, the categorization approach helps professionals distinguish between normal and hemorrhage photos and perform correct picture analysis. The ability of deep learning techniques, particularly convolutional neural networks (CNNs), to handle challenging learning tasks is making them more and more well-liked. The original purpose of CNNs was to support image analysis [1]. Reduced parameter learning is made possible by the convolutional structure, which makes use of the intrinsic relationship between neighboring pixels. CNN network kernels matched the visual attributes that appeared to be essential for finishing the specific classification assignment. Later, this assumption was extended to other data types, such as speech recognition [4], signal processing [3], and natural language processing [2]. In computer vision applications like object identification [5], object localization [6], and segmentation [7], two-dimensional CNNs have become more and more prevalent.

One of the most popular diagnostic procedures in the emergency department for patients with head trauma, stroke, or elevated intracranial pressure is a non-contrast head CT scan. They are a popular first-line diagnostic modality because of their broad availability and relatively fast acquisition time (Ring et al. 2010), and head CT is increasingly being used to rule out the necessity for neurosurgical surgery (Larson et al. 2011). Easily diagnosed on a CT scan, the most serious and time-sensitive anomalies include ICH, elevated intracranial pressure, and cranial fractures. A crucial assessment objective for stroke patients is to exclude an ICH, which depends on CT imaging and how quickly it can be evaluated. Similarly, prompt interpretation of the CT scan is essential in deciding if neurosurgical therapy is necessary for individuals with a suspected acute ICH. Open or depressed skull fractures often need rapid neurosurgical care. On head CT scans, cranial fractures are also the most often missed significant abnormality, especially if they run in an axial orientation.

Organizing the head CT scan by automating the initial assessment and trauma care process may significantly shorten the time to diagnosis and expedite treatment, even if these abnormalities only show up on a small percentage of CT scans. Thus, there would be a decrease in the incidence and mortality of stroke and head injuries. In a scenario where brain injury treatment is provided in a crowded manner, a computer-controlled head CT scan assessment and diagnostic system might help with decision-making in remote locations where medical professionals are not always readily available. (Chilamkurthy et al. 2018).

Benefits include:
- Complete sensitivity in identifying "clinically relevant" acute hemorrhage.
- It is regarded as the benchmark for all diagnostic techniques.

As soon as possible, these illnesses must be diagnosed and treated. ICH is a major public health concern that is associated with considerable death, disability, and long-term mortality. Therefore, it is critical to diagnose ICH using a non-invasive method and to act quickly to determine the best course of therapy in order to save lives. This ought to be feasible even in locations where doctors are not immediately available to diagnose ICH. Reducing the time to diagnosis and accelerating treatment might be achieved by automating the first screening and triage steps in the head CT scan interpretation workflow. In an extremely busy trauma care setting, a computing system that supports automatic brain...
2 Literature Survey

2.1 ICH Studies

Ischemic cardiomyopathy (ICH) is a deadly illness. The vast range of diseases that may cause ICH is reflected in the imaging look of ICH (Heit et al. 2017). Cordonnier et al. (2018) state that acute spontaneous intracerebral haemorrhage is a potentially fatal illness with few known therapeutic options. The aetiology, prognosis, and available therapies for ICH are determined in part by certain clinical and imaging features. Survival and recovery after intracerebral haemorrhage are influenced by the location.
2.2 CT Image-Based Ischemic Heart Diagnosis

Chan and others (2008) Following a head injury, neurological issues are often caused by Acute Intracranial Haemorrhage (AIH). Its existence demands a different kind of administration. AIH is diagnosed in contemporary medicine using brain computed tomography (CT). When the injury is subtle or the reader lacks expertise, identifying AIH may be difficult. Consequently, physicians of different skill levels will benefit from the Computer-Aided Diagnostic (CAD) system, which will help in the diagnosis of AIH, especially small lesions.

Acute intracranial haemorrhage, or ICH, is caused by either exterior (extra-axial) or internal (intra-axial) brain injury (AIH). Small haemorrhages in the extra-axial area might be challenging to differentiate from large bleeds, such as those in the intra-axial region, which are easy to identify. A technique for identifying and detecting ICH and AIH in different anatomical locations using CT images was presented by Pragnya et al. (2009).

A brain haemorrhage is a kind of stroke that happens when an artery in the brain bursts, causing a bleed in the surrounding tissues (Balasooriya et al., 2012). Cerebral bleed diagnosis, which is mainly achieved by analysing a CT scan, enables accurate diagnosis and prognosis in addition to the extraction of strong and trustworthy metrics for patient care. Titano et al. (2018) spoke about how maintaining neurologic function and achieving major improvements depend on early detection and treatment of serious neurological conditions such as internal bleeding, hydrocephalus, and blood clots. Even though these conditions often have easily recognised symptoms, rapid tomography is an essential diagnostic tool. The use of computer-aided monitoring of severe neurologic events in With the potential to prioritise the diagnostic imaging process flow, cranial imaging may expedite therapy and improve results..

In 2018, Monika and colleagues presented a deep learning method for automated brain haemorrhage detection from CT scans, which mimicked the real-world radiologists' approach to assessing a 3D CT image. Additionally, the model combined the slice-level predictions to create a prognosis at the CT level by using the 3D context from adjacent slices to improve quality at each slice. Initial findings on automated ICH identification from CT images may be useful to help the radiologist identify haemorrhages during computer-aided diagnosis (Majumdar et al., 2018).

According to Kuang et al. (2019), a crucial diagnostic imaging assessment tool for the management of ischemic stroke is cerebral infarct volume (CIV), which is determined from follow-up NCCT images of patients with acute ischemic stroke (AIS). Post-treatment cerebral ischemia infarction (CIVI) is often the sole occurrence in NCCT of AIS patients. However, in addition to ischemic infarction, hematoma transition occurs in around 10% of all AIS patients. One of the most often used imaging modalities for mapping brain tissue distributions in vivo is CT, according to Adduru et al. (2020).

Faster execution and diagnostics are made possible via feature extraction from regions of interest, which shortens processing times. Several research focused on ROI-based feature extraction to achieve classification. conducted experiments to extract discriminative features from a brain CT scan's ROI and categorize the results using decision trees, neural networks, and support vector machines. Recognition. On diffusion-weighted (DW) brain images, the regions of ICH have been experimented with using the cosine and wavelet transforms. For feature analysis and classification, the K-Nearest Neighbor (KNN) classifier is employed. The best results were obtained with the wavelet transform.
Every pixel in the image has its homogeneity value calculated, and if any changes are found, the largest change in unique textures is identified. The texture of the abnormal region of the brain is different from that of the surrounding tissue. A significant change in the matrix value increases the likelihood that you may encounter an abnormal area. For brain stroke, Kaggle offers a standard intracranial hemorrhage CT imaging collection. The collection consists of 2501 CT scans, including both normal and hemorrhage pictures. The dataset contains 50 patients without hemorrhage and 30 individuals with hemorrhage. For every patient, thirty CT imaging slices are typically available. The MATLAB R2020b platform is used for the experiments. Every single photo is in.jpg format. The resolution of the original photographs is 640 × 640 pixels. For processing, it has been reduced in size to 256 by 256 pixels. A Gaussian filter is used for preprocessing on the images as they include noise. The Gray Level Co-occurrence Matrix is used to analyze texture characteristics and image-converted features (GLCM). The Machine Learning WEKA tool’s Random Forest, Random Tree, and REPTree Classifiers are used to distinguish between normal and aberrant pictures. Lastly, the accuracy of several categorization techniques is assessed and evaluated.

**Fig. 1.** Displays several picture sets from the dataset.

### 3 Proposed Methods

In this work, we used two networks (1D CNN and LSTM) to analyze and assess many ICH deep learning classifiers. One kind of deep neural network model called a 1D CNN is used to extract the spatial local information of words in a single dimension. It is made up of a convolutional kernel and a max pooling layer [16]. LSTM was used to extract sequential features from the radiological report after 1D CNN was added to the network. An LSTM is a kind of recurrent neural network (RNN). A simple RNN is a neural network module that may be unrolled at various intervals. For text processing, where sequential information is
crucial, RNN is hence useful. Actually, vanishing gradients in lengthy word sequences are not as typical cause of poor performance for basic RNNs [10].

The suggested technique for classifying intracranial hemorrhages incorporates textural information and altered picture characteristics. Preprocessing CT images, transformed feature synthesis and selection, classification, and a comparative analysis of various feature selection techniques for Random Forest, Random Tree, and REPTree classifiers are all included in the proposed research. The proposed hybrid feature extraction method and classification model are shown in Figures 2a and 2b.
3.1 A hybrid feature extraction method for classifying intracranial hemorrhages is proposed.

The suggested feature extraction method makes use of the combined feature set from transformed-based features and GLCM-based features. It's important to recognize the texture of a picture when categorizing photographs from one texture to another, and this may be done by extracting features using a GLCM-based technique. Transformed-based methods also help distinguish the high- and low-frequency coefficients in the input images. Consequently, images that hold important information may be easily obtained from the energy coefficients. By combining these two methods, several hybrid feature vector sets are created, and the classification accuracy of Random Forest, Random Tree, and REPTree classifiers is assessed. This allows for the efficient identification of normal and abnormal images as well as a faster classification process. This section covers hybrid feature selection techniques, GLCM-based features, and modified image-based features. It also covers the use of Random Forest, Random Tree, and REPTree classifiers for picture classification.

3.2 Image-based Features generated for Intracranial Hemorrhage classification

For Image-based Features, the Grey Level Co-occurrence Matrices (GLCM) technique is utilized. Contrast, Correction, Energy, and Homogeneity are all GLCM characteristics to consider.

3.3 Hybrid feature selection approach for Intracranial Hemorrhage classification

A method for choosing features that blends textural and energy coefficient-based features. A set of feature vectors is produced by combining GLCM texture features, DWT transformed feature coefficients, and DCT converted feature coefficients. Ultimately, these feature vectors are sent into the Classification Algorithm, which classifies the images into normal and pathological categories. The hybrid approach to choosing features. The first hybrid techniques that were examined were image-based GLCM features and discrete cosine transform features. The second approach integrates image-based GLCM features together with the discrete wavelet transform.

3.3.1 Proposed Classification Algorithm

A qualified radiologist should assess the radiological findings and evaluate if an ICH diagnosis is feasible [9]. For ICH categorization, a basic keyword search like “ICH” proved insufficient since the average narrative length was just 100 words. The radiologist’s ground truth annotations were significantly more accurate than the PhD student’s. A complex deep learning architecture using 1D CNN, LSTM, and logistic function was created in this work. The vectorized 50 sentences with 300 dimensions were used to train a 1D CNN, which allowed it to extract spatially co-located characteristics. These characteristics served as inputs for the LSTM, which extracted the sequential features from the reports. The LSTM was designed to have a drop out in order to reduce overfitting [19]. The last layer of the LSTM modules included a logistic function that was responsible for categorizing radiological ICH results.
4 Experiments and Analysis

4.1 CNN-LSTM Method:

We used a mix of 1D CNN and LSTM architecture for ICH diagnosis in radiological investigations, and the results were positive (0.94 AUC). In terms of ICH diagnosis recognition, the proposed model performed better than the graduate student, even though it was trained on the identical report that was annotated by the same individual. We found that CNNs can extract significant ICH features even in the presence of inadequate ground truth, a behavior that has been previously shown in a computer vision task using a dataset with poor labeling [15]. To our knowledge, this is one of the first uses of 1D CNN and LSTM for report labeling in subsequent supporting research [23]. In the correct direction, this endeavor is a good step.

Fig. 3. The ICH radiological classification's ROC curve

The purpose of this study was to develop an automated CT scanner that can detect an ICH and mark it as an urgent case for hospital clinical workflow integration in order to improve patient care [24]. As previously stated, this required the tagged 40,000 head CT images that matched the 40,000 ICH reports.

4.2 GLCM Features Extraction Method.

This section covers the outcomes of five different methods of classifying images: Image Features (GLCM) based, DCT transformed features and Image Feature based, DWT transformed features and Image Feature based, and Image Features (GLCM) based. The classification accuracy of DCT converted image features with different k-fold values of 5, 10, 15, 20, 25, and 30 is determined by applying the proposed approach. Machine learning classifiers like Random Forest, Random Tree, and REPTree are used in it. Table 2 shows the classification accuracy of the Random Tree, Random Forest, and REPTree classifiers for various values of k. In all classification approaches, Random Forest performs better than Random Tree and REPTree classifiers. The greatest classification accuracy of the random forest classifier for k=25 is 75.12%.
Table 1. Classification accuracy using DCT Transformed Features with Random Tree, Random Forest, and REPTree classifiers

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Classification Accuracy(%) for K-fold values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>k=5</td>
</tr>
<tr>
<td>Random Forest</td>
<td></td>
</tr>
<tr>
<td>Random Tree</td>
<td></td>
</tr>
<tr>
<td>REPTree</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 4. Comparison of Random Tree, Random Forest, and REPTree classification accuracy using features based on DCT

4.3 Image Features based Classification

Table 2. Classification accuracy of image-based GLCM feature sets for various k values using Random Tree, Random Forest, and REPTree classifier

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Classification Accuracy(%) for K-fold values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>k=5</td>
</tr>
<tr>
<td>Random Forest</td>
<td></td>
</tr>
<tr>
<td>Random Tree</td>
<td></td>
</tr>
<tr>
<td>REPTree</td>
<td></td>
</tr>
</tbody>
</table>
5 Conclusion

The primary discovery of the transformed-based feature technique is the high energy coefficients that were acquired from CT images utilizing the transformed methodology. Compared to the Discrete Cosine Transform, the Discrete Wavelet Transform yields better features and allows for more picture compression. The accuracy of hybrid feature-based categorization for DCT+GLCM and DWT+GLCM is examined. Compared to the transformed feature-based technique and image-based GLCM features, the hybrid features-based method outperforms both. The performance of Random Forest outperforms all other classification techniques. In the future, hybrid feature-based algorithms for big datasets could include new, specialized feature groups. 1D CNNs are used to extract semantically co-located features; LSTM is used to recover the data’s sequential structure; and a logistic function is used to identify ICH in the design. The receiver operator characteristic (ROC) curve is used to assess how well the design’s classification works. The area under the curve (AUC) of 0.94 on the ROC curve indicates that the model worked well. The findings are intriguing in that they suggest that modern deep learning-based algorithms may be used to extract diagnostic information from unstructured medical data. In order to save time, cost, and human error, this project aims to automatically classify 27,148 radiological results.

References

1. Ramdas Vankdothu, Dr. Mohd Abdul Hameed, Husnah Fatima” A Brain Tumor Identification and Classification Using Deep Learning based on CNN-LSTM Method”


