Turkish Journal of Computer and Mathematics Education *Vol.10 No.01 (2019), 602-611*
DOI: https://doi.org/10.17762/turcomat.v10i1.13555

Research Article

An Implementation of Deep Wavelet Auto Encoder-Based Deep Neural Network Brain MRI Image Classification for Cancer Detection

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Abstract
Both computational intelligence and pattern recognition depend on Brain lesion segmentation and classification. In this procedure, an effective algorithm was used to segment the lesion, and its characteristics, including LBP, were paired with the GLCM to extract the data from the picture. A morphologically based fuzzy C-means clustering technique (M-FCM) is suggested for clustering in segmentation. The severity of the information from the brain is then classified using CNN utilising the procedure used in the medical profession to detect brain lesions. The major goals of this procedure are to locate the malignant area on an MRI of the brain and to categorise the severity of that brain in order to increase process effectiveness.

1. Introduction

A tumour is an unchecked cell proliferation in any area of the body. There are several forms of tumours, each with unique traits and therapies. Brain cancers are currently divided into two categories: primary brain tumours and metastatic brain tumours. While the later beginning as a cancer somewhere else in the body and spread to the brain, the earlier start in the brain but frequently remain there. One of the key steps in the planning of surgery and treatment is brain tumour segmentation. An active field of study has been utilising MRI to segment brain tumours. Brain tumours can occur anywhere in the brain and come in a variety of sizes and forms. The automated segmentation of tumours is quite difficult because of the fluctuating intensity of tumours in brain magnetic resonance imaging (MRI). Tumor segmentation on magnetic resonance imaging has been proposed using a variety of intensity-based approaches. One of the most used features for picture categorization and retrieval is texture. The best textural characteristics of a brain tumour are retrieved from the MRI images of the brain using the FCM and JAYA algorithm technique. After classifying the tumour and non-tumor tissues using these techniques, the tumour is segmented. When compared to segmentation techniques based on current practises, this technology segments brain tumours more effectively and yields more accurate results. The abnormal development of tissues is a tumour. A brain tumour is a collection of unneeded cells that is expanding in the central canal of the brain.

Tools and techniques for analysing tumours and their behaviour are becoming increasingly commonplace nowadays. Undoubtedly, the last century's efforts have resulted in significant advancements. But we've also come to understand that improvements in diagnostic tools are necessary to maximise survival benefits. Though a cure for brain tumours has not yet been found, significant progress has been made in this direction. Clinical trials are now being conducted with more and more researchers using measurements, and each new development gives hope to the team of carers and, more significantly, for people with this condition. Particularly in brain imaging, where MRI's soft tissue contrast and non-invasiveness are obvious advantages, magnetic resonance imaging, or MRI, has grown to be a frequently utilised technique for high-quality medical imaging.

Monitoring the size of a brain tumour as it reacts to therapy is a significant application of MRI data. Consequently, a helpful tool would be an automated and trustworthy way for segmenting tumours. A computerised depiction of tissue properties that may be acquired in any tissue plane is provided by MRI. The easiest way to explain the pictures created by an MRI scanner is as slices across the brain. The ability to present images that traverse the brain both horizontally and vertically is an additional benefit of MRI. This makes the MRI-scan pictures a perfect source for locating, categorising, and detecting the right brain areas that are affected. The majority of existing conventional diagnosis methods rely on human judgement when evaluating the results of an MRI scan; undoubtedly, this raises the risk of incorrectly detecting and identifying a brain tumour. However, using digital image processing guarantees the early and accurate diagnosis of the tumour. The segmentation procedure is one of the best ways to extract data from intricate medical pictures, and it is widely used in the medical industry. Picture segmentation's fundamental objective is to separate a picture into mutually exclusive, exhausted portions, each of which is spatially contiguous and includes pixels with homogenous colour a predetermined criterion. Most

instances lack an identified cause. Genetic syndromes such neurofibromatosis, risk factors may occasionally exist and include ionising radiation, exposure to the chemical vinyl chloride, and the Epstein-Barr virus.
The most effective method for identifying brain tumours and tracking their progress after therapy is magnetic resonance imaging (MRI). To tackle the complexity as well as time and objectiveness restrictions, many MRI modalities of each patient are obtained, and these pictures are processed by computer-based image analysis algorithms. This thesis presents two key unique methods for automatically assessing tumor-bearing brain images: To offer quantitative volumetric information, multi-modal tissue classification with integrated regularisation can separate healthy and diseased brain tissues, including their sub-compartments. The technique has been tested on several clinical and artificial pictures with positive outcomes. The algorithm's quick run-time makes it simple to include into the clinical work flow. a modest clinical study dataset from many centres was used to test the feasibility of a suggested extension for integrated segmentation of longitudinal patient studies. The findings were encouraging. It has been demonstrated that segmenting the healthy brain regions surrounding the tumour using atlas-based segmentation with integrated tumor-growth modelling is an effective method. A solution to deal with the missing tumour from the atlas during registration is provided by tumor-growth modelling. Two alternative tumor-growth models have been contrasted for this purpose.
A more complex multi-scale tumour development model demonstrated superior possibility to provide an atlas-based segmentation prior that is more relevant and realistic, even if a simpler tumour growth model had advantages in computing performance. A comprehensive framework for assessing tumor-bearing brain pictures has been created by combining both methods and employing all of the imaging data that is often accessible in clinics. This segmentation approach paves the path for improved brain tumour radiation and neurosurgery diagnosis, planning, and monitoring.

2. Literature Survey

In this article, we offer a technique for analysing PAP smear images based on segmentation using histograms and structuring elements as well as a size and shape analysis of the cell nuclei. As was previously indicated, human observation is not always accurate, and according to Marroquin, 61.5% of accessible pathological tests that are manually screened are still unclassified. This study proposes a method for analysing PAP smear pictures of the cervical area based on an examination of the distribution and size and shape of the cell nuclei. An effective and simple approach to find any abnormalities in cervical cells is the PAP smear test. However, analysing a lot of PAP smear photos by hand is a laborious operation and human inspection is not always gratifying. This study's objectives include automating the screening procedure and providing detailed statistical information that will be useful in identifying anomalies in the cervical area. It is possible to programme MATLAB to discriminate between normal and suspect cervical cells by examining the distribution of cell nuclei and taking into consideration aspects of form and size [1].
This study was started in order to make a contribution to the field by identifying and maximising the presence of cancer cells in lungs. When cancer patients are treated when it is still treatable, there are not only more treatment choices accessible, but also higher survival rates. One of the most common and major causes of mortality globally is lung cancer. It has the lowest survival rate following diagnosis and is the second most chronic condition in both men and women. Therefore, it is essential to forecast and diagnose lung cancer at an early stage. The different methods for detecting lung cancer nodules were compared in this study along three dimensions, encompassing imaging modalities, image processing methods, and genomics analysis. In order to identify lung nodule cancer using medical imaging, many existing image processing approaches have been compared. Additionally, genetics is a major factor in the emergence of lung cancer. A summary of the genetics structure with prospective genes for lung cancer diagnosis and risk assessment was also provided [2].
As the increase in automatic breast cancer diagnosis utilising image processing, we are going to provide a wonderful approach to identify breast cancer stem cells for an image in this work. A crucial imaging diagnostic technique for the earlier identification of brain cancer is magnetic resonance imaging (MRI). One of the most deadly illnesses that affect people frequently is brain cancer. If the cancer is discovered in its early stages, the prospects of survival can be boosted. Radiologists rely heavily on MRI brain images to access patients for diagnosis and therapy. Radiologists must spend a lot of time and effort studying medical images, and their proficiency determines how accurate they are. This study discusses the merits and limitations of the many existing

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approaches of segmenting brain images through automated algorithms that are precise and require little user input. This review article offers advice on how to combine two or more procedures to reach an accurate outcome [3].
In this study, the threshold operation, watershed segmentation, and morphological operation are used to identify cancer cells. The cancer cell will be found when the picture has been analysed using morphological methods. One of the most complex and developing areas of study nowadays is medical image processing. Magnetic Resonance Imaging (MRI) processing is one of the components of this area. Multispectral MRI has become a viable replacement to ultrasound (US) imaging in recent years for the accurate detection of cancer in the breast, prostate, liver, and other organs. Physicians believe that the most effective imaging technique for identifying cancer existing in multiple organs is magnetic resonance imaging (MRI). As a result, MR imaging analysis is necessary for accurate illness diagnosis. This suggested approach includes some noise reduction, segmentation, and morphological functions, which are thought to be the fundamental elements of image processing. Using the MATLAB programme, cancer cells are found and extracted from MRI prostate images [4].
The goal of this job is to identify any cancer cells that may be present in a bodily component. The procedure involves taking a digital image of the afflicted region and processing it to provide morphologic patterns that distinguish between normal and cancer cells. Early diagnosis of cancer illness is a challenging issue since it can be lethal if it is not discovered in the early stages. The current medical treatments that are utilised to identify cancer in body parts are laborious and need additional laboratory work. The goal of this job is to identify any cancer cells that may be present in a bodily component. The procedure involves taking a digital photograph of the afflicted region and processing it to create a morphological pattern that distinguishes between normal and cancerous cells. The method is distinct from ocular inspection and the biopsy procedure. The depiction of cellular structure with high resolution is made possible by image processing. The purpose of the effort is to use image processing techniques to take advantage of the variations in cellular organisation between malignant and normal tissue, enabling automated, quick, and accurate diagnosis [5].

3. Proposed System

For the early identification of brain tumour patients, brain MRI is crucial. The radiologist must spend a lot of time creating the medical picture, and the correctness of the image is dependent on expertise. As they get around these restrictions, computer assisted systems become increasingly important. There are a number of automated ways, however it is very difficult to automate this procedure since the tumours appear differently in various people. The identification of brain tumours using MRI images uses a variety of feature extraction and classification techniques. In this procedure, we suggested the k-means clustering technique, and the GLCM subsequently does effective segmentation and feature extraction. This technique produces fine segmentation, which is followed by feature extraction that stabilises the image's features.

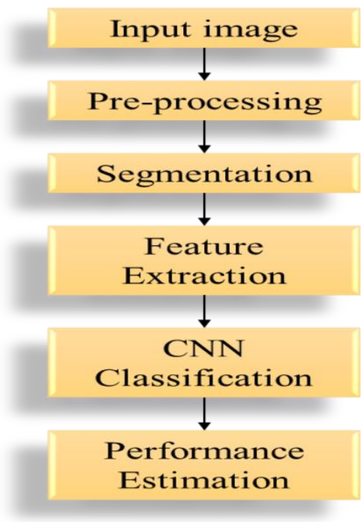

Fig 1: Block Diagram

The following is a list of the suggested approach's benefits:

- The zones with the identical characteristics that we describe may be appropriately separated using this approach.
- This technique may deliver the original photos with crisp edges and effective segmentation outcomes.
- It not only illustrates all relevant characteristics of brain tumours in great detail, but it also encourages medical professionals to learn more about how they work in order to develop more effective treatments.
- It is quite effective and enhances segmentation outcomes.

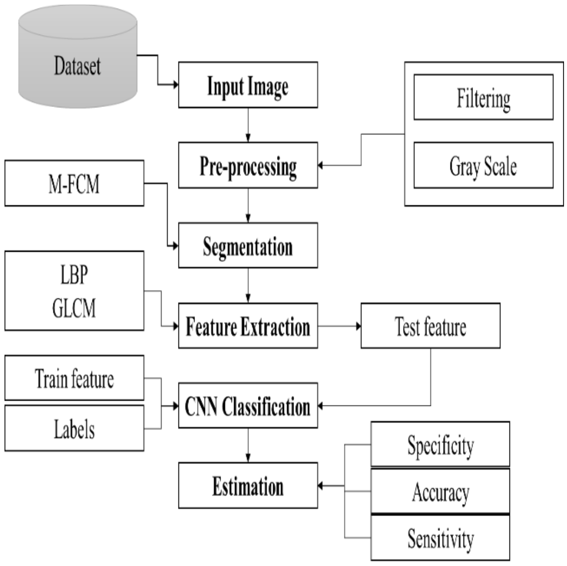

Fig 2: Flow Diagram

1. Input image

The imread command can be used to read an image into the workspace. The example reads a picture, which is one of the sample images supplied with the toolbox, and puts it in an array referred to as I. The graphic file format is Tagged Image File Format, according to what the imread deduces from the file (TIFF). Use the imshow function to display the picture. The Image Viewer software also lets you see images. The imtool function launches the Image Viewer application, which offers a unified setting for viewing pictures and carrying out certain standard image-processing operations. The Image Viewer app gives users access to a number of additional tools for browsing and studying photos in addition to all the image display features of imshow.

2. Pre-Processing

In computer graphics and digital imaging, resizing a digital image is known as image scaling. The expansion of digital material is known in video technology as upscaling or resolution improvement. By applying geometric modifications to the visual primitives that make up the image, it is possible to enlarge a vector graphic image without compromising the image's quality. Scaling raster graphics pictures requires making a new image with more or less pixels.

With the help of image processing, problems like the buildup of noise and signal distortion may be avoided by applying a much wider range of algorithms to the input data.

3. Segmentation

One of the most promising fuzzy clustering techniques is fuzzy c-means (FCM). Despite being a widely used clustering technique, fuzzy C Means fails to produce huge spherical clusters. The FCM can only successfully cluster "spherical" clusters since it only uses squared norm for classifying similarity between data points. However, a variety of clustering algorithms may be produced using FCM to cluster a larger dataset. The major goal of this KFCM is to correctly transform the input data into higher-dimensional feature space, which enhances the likelihood that patterns in the feature space can be separated linearly before performing FCM in the feature space. Another benefit of the KFCM is that it estimates the number of clusters in the dataset.

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4. Feature Extraction

A well-known statistical tool for obtaining second order texture data from photographs is the GLCM. The quantity of distinct grayscales or pixel values depicting that surface is equal to the number of rows and columns in a matrix known as a GLCM. In the region under inquiry, the frequency of one grey level occurring in a certain spatial linear connection with another grey level is described by the GLCM matrix. The GLCM is a tabulation of how frequently certain combinations of grey levels co-occur in an image or image portion given an image with each having an intensity. Calculations of texture features employ the information in the GLCM to provide a measurement of the intensity variation at the target pixel.

5. Classification

Convolutional neural networks are a form of deep, most often, feed-forward artificial neural networks are utilised in machine learning to analyse visual data. CNNs are designed to employ a multilayer perceptron form that requires less preprocessing. They are frequently called shift invariant or space invariant artificial neural networks because of their shared-weights architecture and translation invariance capabilities. Owing to how closely the neuronal connection arrangement resembles the animal visual cortex's architecture, convolutional networks were inspired by biological processes. Individual cortical neurons only react to stimuli within the limited region of the visual field known as the receptive field. To completely cover the visual field, the receptive regions of several neurons partially cross over one another. Due to the reliance on human labour and prior knowledge being reduced while designing features is a significant benefit.

6. Performance Measures

A binary classification test, sometimes referred to as a classification function in statistics, may be evaluated statistically for its sensitivity and specificity.

Sensitivity is the proportion of genuine positives that are accurately identified as such, for example, the proportion of ill those who have been properly identified as having the illness. Other names for the Sensitivity, true positive rate, the recall, or probability of detection in various fields.

The degree to which True negative rates, also known as specificity, are a measure of how accurately real negatives are identified, such as the proportion of healthy people who are correctly categorised as not having the illness.

4. Results

Medical picture interpretation has always taken time, and managing them is difficult in and of itself. The answers presented in this study prompted us to consider DNN, AE, and wavelet transformation from several angles. The major goals of this method are to locate the malignant area on an MRI of the brain and to categorise the severity of that brain in order to increase the process' effectiveness. When compared to current classifiers like DNN, AE, and others, the suggested DWA-DNN classifier has shown excellent outcomes with regards of accuracy,, specificity, sensitivity, and other performance measures. The suggested DWA-DNN technique's findings demonstrate that it outperforms all other non-deep learning strategies when it comes to precision and statistical measurement.

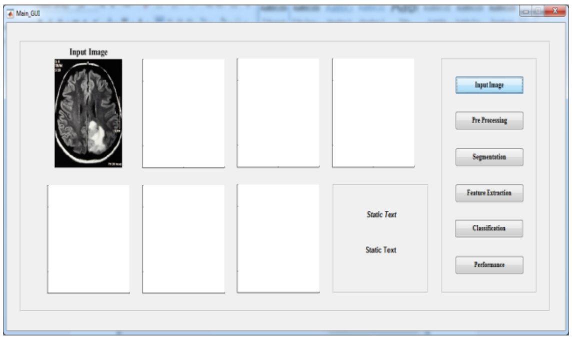

Fig 3: Input Image

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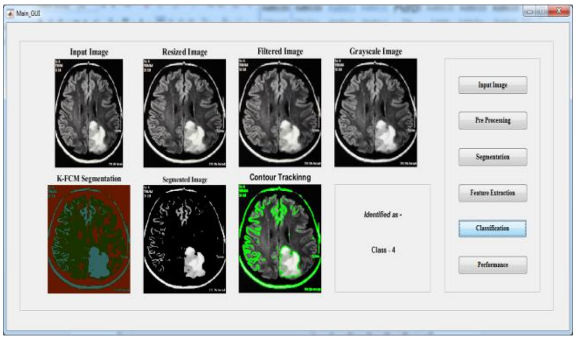

Fig 4: Classification

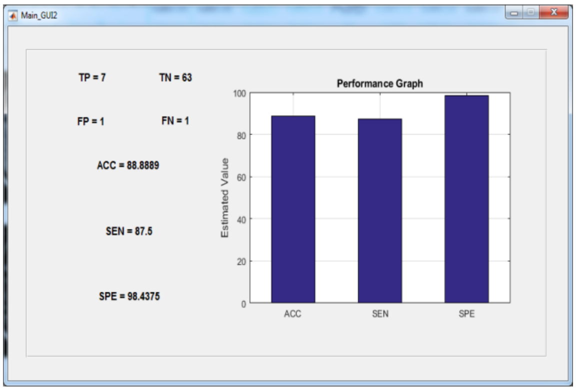

Fig 5: Performance Analysis

5. Conclusion And Future Scope

Medical picture interpretation has always taken time, and managing them is difficult in and of itself. The answers presented in this study prompted us to consider DNN, AE, and wavelet transformation from several angles. Contrasted with current classifiers like DNN, AE, and others, the suggested DWA-DNN classifier has shown excellent outcomes in terms of precision, specificity, sensitivity, and other performance measures. The suggested DWA-DNN technique's findings demonstrate that it outperforms all other non-deep learning strategies in terms of accuracy and statistical measure. To see the impact or performance in the same brain MRI dataset, it would be significantly more intriguing to investigate the possibilities of mixing the DNN with several alternative variations of the auto encoder.

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