CLASSIFICATION OF BRAIN TUMOR FROM MRI IMAGES USING CAPSULE NETWORKS

Dr. N Badrinath
Professor
Annamacharya Institute of Technology and Sciences, Tirupati
badri2005@gmail.com

Dr. J. Jegathesh Amalraj
Assistant Professor
Government Arts and Science College, Tittagudi, Cuddalore
amal.jas@gmail.com

Mr. J. Sathyendra Bhatt
Assistant Professor
St. Joseph Engineering College, Mangalore
sathyendrab@sjec.ac.in

Dr. Logeshwari Dhavamani,
Associate Professor
St. Joseph's College of Engineering, Chennai
logeshgd@gmail.com

Mr. S. Sakthivel
Assistant Professor
Paavai Engineering College (Autonomous)
ssmay1988@gmail.com

Abstract

There is a frequent tumour called a brain tumour, and early detection of this fatal brain tumour can lead to recovery. The treatment must be determined based on an accurate diagnosis of the type and stage of brain tumour. As a result, brain tumour staging is a significant issue when it comes to developing medical-related automatic detection and diagnosis applications. A deep Capsule Network for medical image classification was developed in this paper employing MR images of brain tumours to achieve great accuracy. A customised deep CNN model based on the Capsule Network is created in this study to automatically detect brain tumours in MR images. Each layer in the Capsule Network receives all the previous levels as input, which aids in the discovery of a wide range of features. Residual blocks are inserted between dense layers to increase Capsule Network performance. More than a dozen magnetic resonance images (MR) from various archives are used in the training and testing process. They found that the Capsule Network is more accurate and behaves well while classifying a brain tumour than other methods. As a result, it's clear that CNN models can be put to good use in medical image analysis software development.
Keywords:
Medical Image Classification, Deep Learning, Capsule Network, Texture Features

1. Introduction

After colon, breast, and lung cancers, brain tumours are the most common types of cancer in the world, and they disproportionately afflict women [1]. This means that people are less informed about the disease, which makes it more difficult to get healthcare treatments due to a lack of awareness and accessibility. Developed countries, on the other hand, have screening strategies in place that make it possible to detect pre-tumorous lesions reliably and effectively, allowing for early detection and treatment. In order to live a healthy life and protect everyone, screening and vaccination are the greatest methods for reducing the prevalence of brain tumours [6] [7].

However, early detection is challenging due to the tumor lack of symptoms and its appearance at a later stage, when it poses a threat to spreading throughout the body. As a result, early detection screening is critical for improving survival rates.

A successful method to reduce disease-related morbidity and mortality is brain screening [8]. This depends on a variety of criteria, including the ability to locate screening facilities, quality of screening tests and adequacy of follow-up, in addition to early detection and treatment of any lesions identified [9]; the success of screening. Only a few qualified health workers are available in low and middle-income countries, and the healthcare resources required to continue the screening programme cannot be sustained [10] [11].

Medical professionals now use artificial intelligence and machine learning [14]-[30] to classify disease cases more accurately. Disease prevalence ratios rise, and machine learning solves the classification difficulty connected with disease diagnosis by optimising the classification process.

Adapting the capsule network for medical image classification is the goal of this study, which tries to predict the presence of a brain tumour. Image classification challenges have shown the capsule network to be particularly fruitful. It showing in terms of deducing structural
information from images. Most objects with these kinds of structures create their complex features by combining local ones like curves and edges, such as those found in the real world.

This technology has recently been used for brain tumour segmentation [2], tumour screening [3], diagnosis [4] and segmentation [5] in medical imaging analysis. Medical images can be classified using the Capsule Network, and traditional models find that they operate well with this type of data. Deep networks are widely used in image classification and recognition because of their great accuracy. Increasing the number of layers and experimenting with different combinations improved performance significantly.

This research uses a Capsule Network to address the image classification problem connected with MR images of brain tumours and adapt an image classification challenge.

The paper is organized as follows. Literature survey is given in Section 2. The methods are described in Section 3. Section 4 provides the evaluation of classification. The conclusion is given in Section 5.

2. Literature Survey

Classification of tumorous and normal cells in medical images is a critical step in determining the most effective treatment. The classification of an object using the Capsule Network in the literature is the subject of numerous articles.

The authors in [6] used Capsule Networks to improve classification accuracy when working with small data. This research adds to our understanding of the similarities and differences between CNN and Capsule Network topologies. This was followed by a thorough examination and discussion of the data using uncertainty analysis and probability maps.

The authors in [7] developed a full local connection with transform matrices to Capsule network. Overfitting is more common when using large numbers of training samples, although a previous investigation indicated that the smaller number of convolutional network parameters accessible in Conv-Capsule may alleviate this problem.

The authors in [8] implemented the Capsule Network algorithm to verify the categorization quality of font styles. Font classification has been made easier using this new approach. These aspects are examined in the performance assessment, which also makes public the alphabet and character spacing.
The Capsule Network on hyper-spectral image (HSI) classification with maximum correntropy in [9], which reduced outliers and noise. As a result, the model becomes more reliable and generalizable. For data fusion and categorization, the Capsule Network framework depends on a strong, enlarged version of the Capsule Network. To demonstrate how effectively our deep learning models, outperform the competition, we employed HSI, which was derived from three well-established hyperspectral datasets.

The authors in [10] developed a Capsule Networks variation that is faster and simpler than CNNs by using a novel algorithm. A recurrent Capsule Network is a bi-directional long short-term recurrent structure constructed on top of a Capsule Network, using information acquired in films of microscope samples. According to the findings, the Capsule Network achieves a 93.8% accuracy rate and consistently outperforms CNN under time constraints.

Using images of sick tissue and the capsule network, the authors in [11] developed a useful system for classifying and identifying tumour cells. By utilising training data, the Capsule Network can discover patterns that can be put to good use in many applications. This aids in the early detection of tumours and the identification of the underlying cause is required for the disease to be cured. By doing so, the tumour will be advanced to the point where it is no longer active.

Researchers of [12] analysed the design of the capsule network to recognise iris and developed a deep learning system based on it called Capsule Network to do so. We made structural improvements to the network and established a route between the capsules to ensure that the network works properly for iris recognition. When the number of samples is limited, the deep learning method can be used. We divided the overall network topology of the three networks into subnetworks based on the blocks that made up each network.

The authors in [13] suggested a Capsule Network to adapt CAD models to new domains. Each capsule net on an extractive feature embedding extraction network has the same purpose: to extract feature embeddings from a target domain by combining training information into an artificial memory set of that domain. Capsule Network is flexible enough to work in a variety of settings thanks to its tiny annotated sample size.

Clearly, this demonstrates the necessity for image categorization automation, but it also demonstrates the fact that work is still being done in that field. Tumor categorization from medical imaging can be automated using a variety of methods described in the literature.
Recent advances in deep learning ideas have made it possible to classify medical images automatically.

3. Methodology

Radiologists face a severe limitation when it comes to the classification of brain tumours because of the variance within classes and the similarities across classes in MR images. A CNN-based tumour classification engine using Capsule Network for MR brain tumour classification is proposed to help radiologists. Figure 1 depicts the proposed system workflow. As a result of fine-tuning, the Capsule Network model delivers excellent outcomes.

3.1. Preprocessing Technique

Preprocessing involves removing noise from MR images and boosting contrast for better object recognition in images of brain tumours.

3.1.1. Noise Removal

Digital images may have noise, which is the presence of information that is not intended to be there. To aid in the diagnosing process, clear images are required. In order to remove noise from the original MR images, one must first identify the source of the noise. Depending on how much noise is present, the images may be distorted or contain features. An image noise
can be divided into several types based on the image input data source. Filters are used to reduce noise in the images that are being captured. Images are enhanced by filters in image processing because they reduce undesirable frequencies and smooth the image.

Adaptive filters minimise noise without altering the original image in any way. When pixels are modified during filtering, statistical parameters are evaluated and adjusted accordingly. To reduce the amount of noise, we employ an adaptive median filter in our research. Find the filter size median, lowest, and maximum values. After that, it compares each pixel value to see if it should be replaced or not. Then broaden the filter window to accommodate the new data. Only pixels with noise content are subject to the adaptive median filter. It works effectively with both low and high noise densities. Figure 2 depicts the adaptive median filter in action.

![Figure 2. Filtering output (a) Original image (b) After filtering](image)

### 3.1.2. Contrast Enhancement

The quality of an image is critical when it comes to medical imaging because it can help doctors diagnose disorders. Tumor staging is complicated by the varying densities of different tissues. Tumor tissue can be detected more easily by utilising contrast enhancement techniques such as Contrast Limited Adaptive Histogram Equalization. The use of contrast enhancement brings forth the tissue varying density to the forefront. The CNN model can also create features for classifying MR images using the information provided by this feature set. We apply Adaptive Histogram Equalization to boost the MR image intensity with contrast enhancement on images. With Adaptive Histogram Equalization, the Intensity Enhancement effect can be visualised in Figure 3.
According to the findings, a new design called the Capsule Network may accurately identify benign and malignant tumour cells in imaging data. An entire network of caps is considered to be a single neuron, with each cap representing an individual parameter. These neurons' vector length suggests the existence of the aforementioned particular object. The Capsule Network overcame CNN pooling layer issue, and changes to the pooling layer architecture increased the network classification performance. There may be differences across repetitions in terms of coupling coefficients, even if the parent capsules are the same. As a result, the parent capsule sorts the event by raising the coefficient between the capsules, where the forecast matches the parent capsule output.

**3.2. Capsule Network**

(a) Before enhancement

(b) After enhancement

Figure 3. The output of CLAHE
In view of capsule $u_i$ output $i$, the parent capsule $j$ is estimated using the process of classification:

$$u_{ji} = W_{ji} u_i$$

Where

$u_{ji}$ is regarded as the prediction of a vector from the capsule output $j$,

The capsule $i$ estimates the vector prediction, and

$W_{ji}$ is regarded as the weighting matrix applied specifically with backward pass.

The Capsule Network uses the agreement level between the capsules in the following layer to couple coefficients $c_{ij}$ using the Softmax function.

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{kj})}$$

where

$b_{ij}$ is the log likelihood function and it functions when the $i^{th}$ capsule is connected with $j^{th}$ capsule and it is set to 0 at the initial iteration.

The following is an estimate for the input capsule vector $j$:

$$s_j = \sum_i c_{ij} u_{ji}$$

It employs a non-linear function that exceeds the output vector of each capsule and then uses the initial vector to get the output, where its non-linear function is defined as follows:
\[ v_j = \frac{\|s_j\|^2 s_j}{1 + \|s_j\|^{2}} \] (4)

where,

\( s_j \) is the input of \( j^{th} \) capsule and

\( v_j \) is the output of \( j^{th} \) capsule.

For example, if a non-linear function \( v_j \) is used in the classification process, then the log likelihood is updated based on how well the output capsule vectors agree with each other. If this happens, an internal product is then produced.

The study uses an agreement function to keep the coupling coefficient up to date in the pooling layer and log probability.

\[ a_{ij} = v_j \cdot u_{ij} \] (5)

The loss function \( l_k \) in the last layer capsule \( k \) is designed to provide a higher level of precision in anticipating the occurrences. The following is an estimate of the loss function \( l_k \):

\[ l_k = T_k \max(0, m^+ - \|v_k\|^2) \lambda (1-T_k) \max(0, \|v_k\| - m^-)^2 \] (6)

Here

\[ T_k = \begin{cases} 1 & \text{if } k \text{ exist} \\ 0 & \text{if } k \text{ does not exist} \end{cases} \]

The hyperparameters such as \( (m^+, m^- \text{ and } \lambda) \) are thus estimated throughout the training phase.

A regularisation function is used in the Capsule Network model to mitigate difficulties associated with over-fitting when the Capsule Network parameters are being trained. As a result, the input is allowed to be encoded as much as feasible by the capsules, and the reconstruction is carried out by feeding a neural network with 16D output from the output capsules.

4. Results

For the classification of images of brain tumours, a comparison will be made between the suggested Capsule Network model and traditional CNN models in this section. Below, you'll see the results of the analysis on a number of different imagegraphs.
Finally, we used an NVIDIA GeForce GTX 1080 with 8 GB of RAM to run the suggested Capsule Network-Capsule Network paradigm. 20,000 images are used for training, validation, and testing. Capsule Network receives input for DICOM images via the pydicom python module and processes them.

For this project, we used MR images of brain tumours that were retrieved from the Kaggle repository (https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection).

Brain tumour classification using the proposed Capsule Network compares favourably with standard deep learning classifiers. Here are some metrics for testing the suggested approach, which is based on a 5-fold cross validation model:

\[
\text{Accuracy} = \frac{TP}{TP + TN + FP + FN}
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\]

\[
\text{Specificity} = \frac{TN}{TP + TN}
\]

\[
\text{F-measure} = \frac{TP}{TP + 0.5(FP + FN)}
\]

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right|
\]

Where,

- \(n\) - Total iterations
- \(TP\) - True Positive
- \(FP\) - False Positive
- \(TN\) - True Negative
- \(FN\) - False Negative
- \(A_i\) - Actual value
- \(F_i\) - Forecast value
(a) Training Accuracy

(a) Testing Accuracy
Figure 5: Accuracy

As shown in Figure 5, the Capsule Network classifier outperforms traditional deep learning classifiers in terms of accuracy. The Capsule Network classifies input images and uses five-fold cross validation in supervised learning with a greater number of training examples. Compared to previous models, the proposed classifier performs better in testing.
Using a traditional deep learning classifier and the Capsule Network classifier (Figure 6), the F-measure is shown. Using five-fold cross validation and training on many images, the Capsule Network achieves a higher F-measure rate in terms of more specificity and sensitivity. According to the results of the tests, the proposed classifier has a higher F-measure rate than the competing models.
Figure 7 compares the Capsule Network classifier MAPE performance to that of traditional deep learning classifiers. The Capsule Network classifies brain tumours more accurately than other methods thanks to five-fold cross validation iterated with a sigmoid loss function. This classifier has a lower MAPE than other models, according to the results of the testing.
Figure 8: Sensitivity

As can be seen in Figure 8, when compared to more traditional deep learning classifiers, the Capsule Network classifier is far more sensitive. It is possible to retrieve more true positive examples in a five-fold cross validation by using the Capsule Network multi-label classification of input images. According to the results of the testing, the proposed classifier is more sensitive than other models.
As can be seen in Figure 9, the Capsule Network classifier is more specific than the deep learning classifiers it replaces. With the Capsule Network, input images can be labelled with multiple labels, making it possible to accurately classify true negatives using a five-fold cross-validation process. This classifier has a greater rate of specificity than other models, according to testing.

4. Conclusion

A new Capsule Network model for categorising brain tumour MR images was developed in this study. It has a 93.54% classification accuracy for brain tumours. Taking everything into account, the Capsule Network model was able to achieve greater classification accuracy thanks to numerous configurations of network architecture with various hyperparameters. An algorithm developed by Capsule Network researchers may increase the accuracy of tools for image classification used by clinicians. As a result, diagnostic accuracy rises, making treatment planning easier in the healthcare industry.
References


