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CLASSIFICATION OF BRAIN CANCER TYPE USING MACHINE LEARNING

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Abstract: The Brain cancer is the most dangerous and found commonly in multitude of people in the younger stage and the adolescent stages. The early stage identification about the tumors in the brain and the appropriate type of the cancer would help the physicians in deciding the accurate treatments and further analyzing based on the responses from the patients to the treatment done. The paper puts forth the capsule neural network, the machine learning system that can be trained using a less number of dataset unlike convolutional neural network and is sturdy against the rotation or the affine conversions, to identify the type of cancerous tumors in brain at its early stage. The evaluation of the training and the testing accuracy of the proposed method for classification of the brain cancer type using the capsule neural network proves that Caps Net based classification have outperformed the convolutional networks.

Keywords: Brain Cancer, Machine Learning, Convolutional Neural Network, Capsule Neural Network, Classification, Magnetic Resonance Imaging.

1. INTRODUCTION

The brain cancers serve as the most important reason for the death in the human being. The disease is affects the person as the cells in the brain keep on growing in an uncontrollable fashion. The brain being in charge of every action of your body controls all the voluntary actions such as the vision, hearing, speech and all other activities can be termed as the central processing unit of the body. The figure.2 below shows the structure and the functions handled by the brain. The growth of the cancer cells in the brain causes damages in the parts that administer the activities, leading to many health disorders such as the head ache, problems in vision, and difficulties in hearing, seizure and balancing issues.

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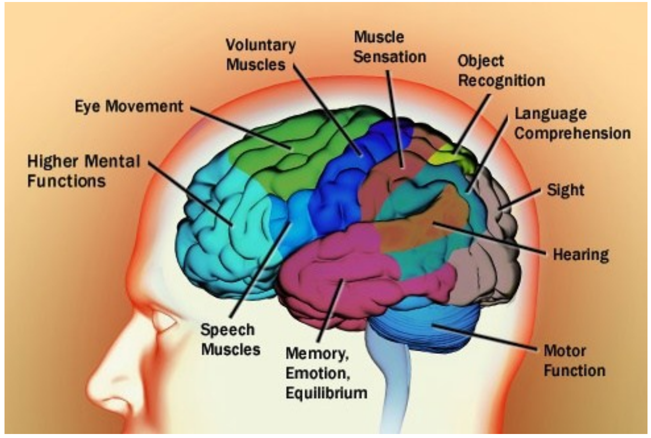

Fig .1 Structures and Functions of Brain

Based on the statistics provided by colorectal cancer center, every year Siegel [1] the number of persons affected by the brain cancer and the death rate caused by it are keeping on increasing among the people of age around 4 to 50. It is counted as the highly deadly disease that could not be treated at ease. The cancer in the brain caused due to the malignant tumor growths is likely to spread among to other parts of the body resulting in mortality. The early diagnosis could help in reducing the severity of the disease by providing a proper treatment to which the patient's body responses.

The most prominent method utilized in identifying of the brain cancer is image processing, the some of the prevailing methods utilizes the artificial neural networks; GLCM based ANN, ResNet model relying on the CNN and the CNN, the problem encountered in the prevailing methods due to the more number of data set requirement for training and improper handling of the input transformation's

The paper puts forth the utilization of the capsule neural networks in classification of the type of the brain cancers to identify the disease in the early stage and avoid fatalities. The contributions of the paper include the

- Recognizes the Cancer type from the collection of Magnetic Resonance Images provided
- Identifies the over-fitting problem in the Capsule neural network for the MRI data set.
- Ensures an efficient training for the capsule network with the data set acquired from the open database.

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- Evaluating by testing the proposed system using the TCGA-GBM (cancer genome atlas glioblastoma multiform) data collection in the cancer imaging archive dataset

The paper as follows is arranged with the 2.Related Works, 3. Proposed Work, 4, Results and Discussion and 5. Conclusion.

2. RELATED WORKS

Sauer, et al [1], presents the "Updated review of prevalence of major risk factors and use of screening tests for cancer in the United States." Siegel, et al [2] provides the "Colorectal cancer statistics, 2017." Özyurt et al [3] the author explores the "neutrosophy and the convolutional neural network to segment the brain images and classify them as the benign and malignant" each stages involved of brain tumor identification proceeded with the involvement of various approaches such as the neutrosophy and EMFSE (expert maximizing fuzzy sure entropy) for segmenting classification employing CNN clubbing the SVM and the KNN Classifiers. The fig.2 represents the overview of the CNN structure.

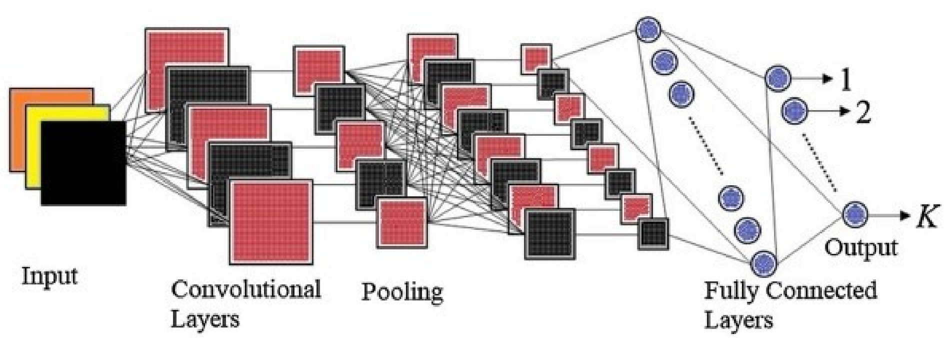

Fig .2 Overview of Structure of CNN [3]

Balasooriya et al [4] the authors extends his work in classifying the images of the of the brain obtained from the MRI to diagnose the presence of cancer cells in it by proposing a deep learning algorithm utilizing the Convolutional neural network. Sajjad,et al[5], the CNN incorporated with the deep learning techniques is utilized for the multi-grade brain tumor classification by segmenting the affecting areas using the deep learning techniques and classifying the tumors grade employing the convolutional neural network, the approach provides a grade

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classification for thebrin tumors. the Sapra, et al [6], the approach put forth in the paper utilizes the probabilistic neural network model that relies on the learning vector quantization to provide an automated brain disease classification using the images obtained from the MRI scans. Kumar et al [7], cancer detection in the brain utilizing the early prediction method employing the texture features along with the neuro classification logic is put forth in the paper, to enhance the accuracy percentage by 50 to 60 percentages than the prevailing classifiers. Joshi,et al [8], the paper present the concise overview to the brain cancer and the classifies the images with the malignant tumors using the artificial neural network .Jain et al [9], proposes a "GLCM based feature extraction for the classification that relies on the ANN for identifying the brain cancer. Ghosal et al [10], the paper utilizes the automatic tool based on the ResNet frame work that relies on the CNN to classify the brain MRI data for the early diagnosing of brain tumor. Khan et al[11], the study based on the two different dataset health and malware classification utilizes the different model of the ResNet 18,50,101,152 to classify the cancer cells as well as the detecting the malware. Shahroudnejad et al [12] the author proceeds with the "investigation and the examination of the structures and the characteristics of the capsule networks and highlights the potential capability of the same, the author further replaces the architectures of the deep learning into the networks with high transparency by alternating the CNNs involved in each layer with the capsules.

3. PROPOSED CAPSULE NETWORK BASED CLASSIFICATION FOR BRAIN CANCER

The capsule [12] neural network unlike the convolutional neural network is comprised of capsules that hold a group of neurons. The activity vectors that are found in the capsules disclose a particular entity type parameter that is utilized for instantiation that might be a part of a whole object or an object whole. It could also be explained in terms of computer graphics that converts the whole task to be performed into smaller parts using the transformation matrix. But the process involved in the capsule network is just the reverse; the network works on the single position of the whole task and converts it to a position of an entire task using the inverse matrix.

Even the posture of the each subparts of the inputs are carefully learned using the Caps Net. It takes into consideration even the orientation and the position of the task fed as the input. As the other frame works such as the CNN, NN and the ResNet do not consider this. For e.g.: The CNN frame works lose the positions of the sections in the input due to the pooling or the subsampling operations and in turn loses much percentage of the entire input that is fed. The capsule utilizes the routing mechanism to mine the high level of information's from the low level of the visual data unlike the convolutional neural network that utilizes the filter to extract the same.

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The capsule networks similar to the human brain has the ability to simplify the data or recognize the data using the very small amount of data utilized for training as they are translation equivariant. But the CNN [3] ANN [7] and the ResNet [11] are translation invariant and require more number of data for training. The probability that an entity exists is denoted by the activity vectors length, and the orientation denoted the instantiation parameters. So the capsule provides the vector whereas the neuron provides the values. The CapsNets are found to be much better than the other frame works used in classification even in the recognizing the highly overlapped information's. The routing –by agreement enables the lower level capsules to pass its output to the high level capsules that has as activity vector with bigger scalar product for the prediction that was routed from the low level capsules.

The paper in order to classify the type of the brain cancer utilizes the Caps Net architecture on [12] the architecture frame is shown in the fig .3 the frame work consist of an input layer followed by a general convolutional layer that engages the activation vector to reshape the inputs received using the squashing function. Further the frame work proceeds with the primary capsule layer followed by the digital capsule layer that present its output to the fully connected layer.

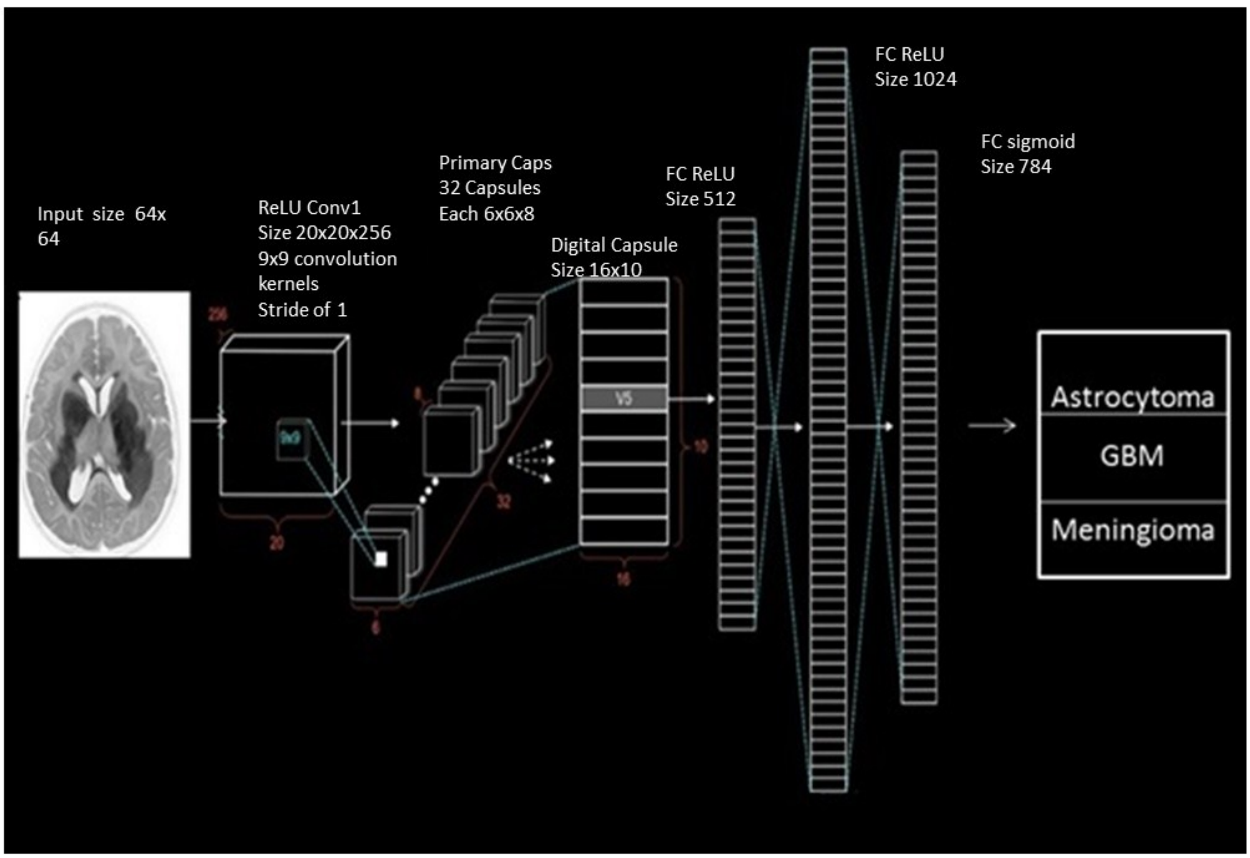

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Fig.3 Capsule Network Architecture

The ReLU nonlinear transfer function and the squashing function are fed represented as shown in the equation (1) below.

$$O_j = \frac{\|C\|^2}{1+\|C\|^2} \frac{C_j}{\sqrt{\int C_j^2 + \gamma}} \tag{1}$$

A small alteration is included to the equation (1) for the general squashing function that is presented in the equation (2) shown below.

$$Oj = \frac{\|C\|^2}{1+\|C\|^2} \frac{C_j}{\|C_j\|} \tag{2}$$

Where Oj is the output of the capsule j and the C_j is the zero vector shared. To avoid the undefined results when computing the equation (2) and to avoid the division with the zero, the $\sqrt{\int C_j^2 + \gamma}$ is added instead of the $\| C_j \|$ and a small value γ is included, where the$\gamma = (1e - 6)$.

The dimension defined for the activity vector can be one or more than it and its length represent the determined probability that an entity exists and also the dissimilarities in the feature of the input image such as the orientation, the line thickness and shape etc. The input that is reshaped and squashed is send to the primary capsules and the digital capsule layers utilizing the dynamic routing algorithm that operates between the primary and the digital capsules.

The capsules try to transfer output vectors to the capsule that is placed above them. Finally the information are decoded and constructed back without any losses. So the capsule network finds it application in area of the object detection, classification and the image segmentation. It proves to have an improved accuracy with the less number of training data involved. But the capsules network finds difficulties in differentiating the very close object. The paper is to continue with the issue faced by the capsule network in the future work.

4. RESULT AND DISCUSSION

The capsule network for the classification of the cancer types in the brain is trained with open database using the Adam optimizer with the parameter .0001 to train the whole network and tested applying the TGCA-GBM dataset from the TCIA. The training and the testing accuracy along with the prediction time for capsule networks and the other frame works such as the CNN, NN and the ResNet are measured and tabulated in the table .1 shown below.

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The fig .4 below shows percentage of the training and the testing accuracy achieved by the capsule and the other frame works in classifying the cancer type in the brain.

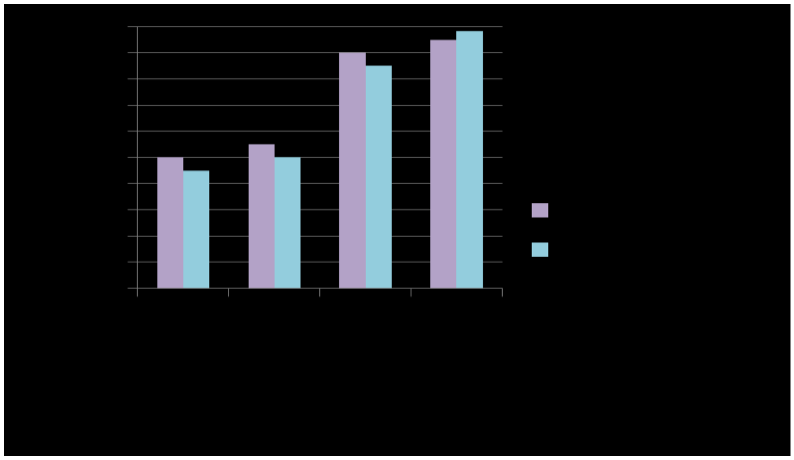

Fig .4 Training and Testing Accuracy

The Table.1 below shows comparison of the accuracy in training, testing and the prediction time consumed by the each model , the results attained shows that the capsule network proves to have a much better classification than the other models CNN, NN and the ResNet incorporated with the CNN.

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Architecture	Training Accuracy	Testing Accuracy	Prediction Time
Neural Network	.5050	.4567	1125s
ResNet	.5945	.4983	2156s
Convolutional neural network	.9074	.8543	213µs
Capsule Neural Network	.9847	.9537	128µs

Table .1. Performance Comparison of CapsNet, CNN, NN and ResNet

5. CONCLUSION

The CapsNet is an imminent architecture that could be applied with a broader range of applications associated with the object detection, image segmentation and classification. Compared to the other frame works it shows additional improvement in the accuracy of the classification with the diminished computational efforts and the time taken for the training as well as the prediction process. The capsule neural network is found to be superior even in terms of memory occupancy and operating in real time compared to the other methods. The capsule neural network engaged in the classifying the type of the brain tumors in the paper shows an enhanced performance in terms of training and testing accuracy , and the prediction time utilizing a very small amount of training data compared to the conventional convolution neural networks, artificial neural networks and ResNet. In future the paper is to handle the survey on the challenges encountered by the capsule network on the grounds of identifying the images that are overcrowded, colored and with the higher resolution and put forth the remedies that could be taken to overcome them.

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