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Brain Tumour Identification and Classification of MRI Using Deep Learning Techniques

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ABSTRACT

Deep learning algorithms applied in context to improve health diagnosis are yielding positive results. The World Health Organization (WHO) defines correct brain tumor diagnosis as "the detection, identification, and categorization of the tumor on the basis of malignancy, grade, and type." Detecting the tumor, classifying the tumor in terms of grade and kind, and identifying the tumor location are all part of this experimental effort in the diagnosis of brain cancers utilizing Magnetic Resonance Imaging (MRI). This strategy has been tested by using a single model for classifying brain MRI on various classification tasks rather than a separate model for each classification job. The multi-task classification based on Convolutional Neural Networks (CNN) is capable of classifying and detecting cancers. By segmenting the brain tumor, a CNN-based model can also be used to identify the location of the tumor. The multi-task classification based on Convolutional Neural Networks (CNN) is capable of classifying and detecting cancers. By segmenting the brain tumor, a CNN-based model can also be used to identify the location of the tumor.

Keywords: Brain tumor location identification, multi-task classification, convolutional neural network.

I. INTRODUCTION

The uncontrolled expansion of tissue in the brain that disrupts brain functions is known as a brain tumor [1]. A primary tumor or a secondary tumor might be found in the brain. This classification is based on the tumor's genesis. Brain tumors are also divided into malignant and noncancerous tumors based on their aggressiveness. Low-grade cancers are categorized as "Grade 1 and Grade 2," while high-grade tumors are classified as "Grade 3 and Grade 4." In addition to these classifications, the World Health Organization (WHO) has identified 120 other forms of brain tumors [1]. The most common electronic modalities are ultrasound, computerized tomography (CT), and magnetic resonance imaging (MRI). MRI is primarily employed for brain tumor examination because it gives a three-dimensional evaluation in the 'pivotal, coronal, and sagittal' orientations. According to the World Health Organization, proper diagnosis requires the detection of brain tumors, identification of the malignancy, location, type, and analysis of the tumor's grade. The goal of locating a brain tumor requires tumor segmentation, while the remaining tasks require categorization. The dataset includes information on the presence, grade, location, and type of brain tumor obtained from publicly available resources. In terms of computational resources, equipping individual models for each of these tasks will be difficult. (CNN) based multi-task classification approach and CNN-based brain tumor segmentation for locationidentification.

II. RELATED WORKS

MRI images have been used to diagnose brain cancers in several studies. This section discusses the approaches proposed in prior investigations. These technologies use techniques such as traditional image processing and a machine learning approach based on neural networks to diagnose brain cancers.

The study work done by [1] proposes an approach that equips Threshold-based Otsu's segmentation using Matrix Laboratory (MATLAB), which detects the tumor and segments the tumor location with an accuracy of 95%. In the work of [2,] the Multilayer Perceptron (MLP) with an accuracy of 85 percent and the Support Vector Machine (SVM) with an accuracy of 74 percent are used to classify brain tumors as normal or abnormal. To detect brain cancers using MRI, an automated method has been developed. Statistical feature analysis is used to extract features from tumor images. The brain tumor features are generated using Haralick's features equations, which are based on the Stochastic Gradient Langevin Dynamics (SGLD) matrix of pictures. Precise segmentation of tumors using MRI is the most important procedure in the diagnosis of tumors. The MRI images of brain tumors are processed, converted to grayscale. Then these images are filtered using Gaussian filters, and finally, the tumor location is segmented by using the region-based segmen- tation method. This is implemented in MATLAB and there is appropriate information about accuracy and evaluation metrics. This work is done by S. Akbar et al and it is mentioned that there is no specific efficient strategy for segmentation of brain tumors [4]. Continuous Wavelet Transform (CWT), Dis- crete Wavelet Transform (DWT), and SVMs are used to detect the tumor, segment, and classify them based on malignancy.

This methodology uses different wavelet levels and high accuracy is achieved using CWT. This study by M. Gurbină et al recommends using a hybrid approach for the diagnosis of brain tumors [5]. Multi-modal MRI-based automatic tumor detection algorithm involving skull extrac- tion of T2-weighted image followed by image cutting, anomaly probabilistic map computation, feature extraction to detect the brain tumor. This methodology initially achieves an average accuracy of 90%. This methodology proposed by P. Dvorak et al shows that the accuracy of segmentation can be im- proved by the shape deformation feature [6]. Different wavelet levels are used in this process, and CWT is used to attain great accuracy. M. Gurbină et al. advocate utilising a hybrid technique to diagnose brain cancers in this study [5]. To detect the brain tumour, a multi-modal MRI-based automatic tumour identification system combining skull extraction of T2-weighted image, image cutting, anomalous probabilistic map computation, and feature extraction is used. Initially, this approach yields an average accuracy of 90%. The accuracy of segmentation can be im- proven by the shape deformation feature, according to this methodology described by P. Dvorak et al [6].

R. Ezhilarasi et al. propose utilising a bounding box to detect the brain tumour region and forecast tumor kind. The tumour is classified as malignant, benign, glial, or astrocytoma using this method. Brain MRI images are

trained from scratch using a Faster Region-Based Convolutional Neural Network (R-CNN) and show promising results [7]. High Grade Glioma (HGG) and Low Grade Glioma (LGG) sections of the tumour are detected utilising CNN-based brain tumour segmentation using MRI data. A SVM classifier is used to classify the type of brain tumour, with depth and tumour stage as parameters. [8] presents this methodology in his work. Aneurysms, haemorrhage, stroke, multiple sclerosis, inflammation, hydrocephalus, infections, swelling, cysts, and bleeding are all classified as brain tumours by CNN. [9] proposes a model that yields 99 percent accuracy. D. Divyamary et colleagues offer a Naive classifier to detect brain tumours using MRI images, which has an accuracy of 84 percent [10]. S. Das et al. propose classifying brain tumours using CNN to identify them as pituitary, glioma, or meningioma. To avoid overfitting, this method uses a Gaussian filter before applying the histogram equalisation technique and dropout regularisation to the brain MRI data. After that, CNN is used to classify the preprocessed images achieves 94.39% accuracy and average precision of 93.33%. This study claims that CNN based classification will be suitable for brain tumor diagnosis and other image oriented diagnosis[11].
The majority of the system has merely determined if a tumour is pre-sent or not based on the above studies and approaches. Some have simply pinpointed the tumor's position. There have been few attempts to divide the tumour into different types. To accurately diagnose a tumour, it is important to complete the WHO-defined method, which includes tumour detection, determining whether it is malignant or benign, determining the location, kind, and analysing the tumor's grade.

III. PROPOSED METHOD

CNN-based models were utilised as the deep learning method for identifying, classifying, and locating Brain Tumors. CNN models are commonly employed for picture data because they have a high accuracy rate. A CNN is a hierarchical model that comprises of various architectures in general. When a CNN model is given photos to train, it recognises the image based on the base level. In this proposed architecture, CNN-based models are used in two modules: brain tumour classification and segmentation. The block diagram depicts the system and its modules in visual form. Figure 1 depicts the system's architecture and workflow.

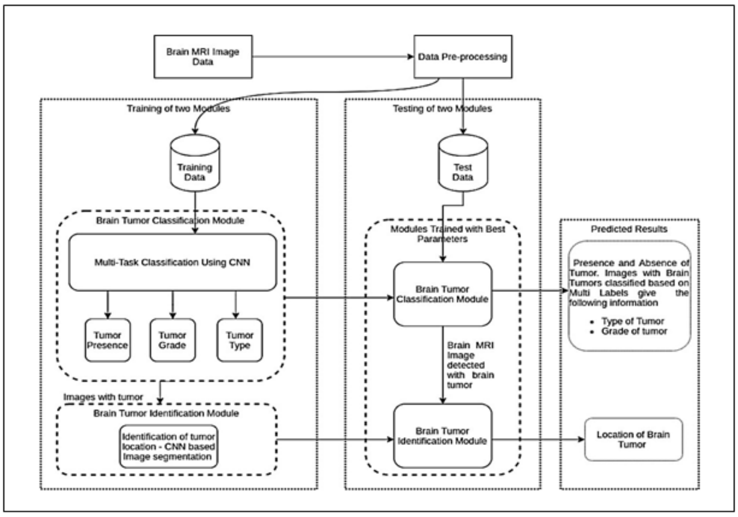

Figure 1. The architecture of the Proposed system

3.1 Dataset Description

The data was gathered via Kaggle Data and the Cancer Imaging Archive. A multilabel dataset is required for this project. To use the provided data to train the data for all of the diagnosis phases and to generate several labels. The following information has been gathered:

- The study's brain dataset comprises of 3064 T1-weighted contrast MR images of 233 subjects. This dataset contains three different forms of malignancies, including meningioma, glioma, and pituitary tumours [12].
- The Glioma Molecular Diagnostic Initiative collected data from 874 glioma specimens, resulting in about 566 566 gene expression arrays, 834 copy number arrays, and 13,472 clinical phenotypic data points [13], [14].
- Kaggle Datasets were used to obtain normal brain pictures.

3.2 Data Preprocessing

Data preprocessing involves processing the raw data to obtain the data in the required format. The raw data collected from various sources in different formats such as Digital Imaging and Communications in Medicine (.dcm), Microsoft Access Table (.mat), Joint Photographic Expert Group (.jpg). The Rembrandt dataset contains the images in .dcm format and the features and labels information is provided in a comma-separated values (CSV) file. Based on the tumor location data in the features file the images containing the tumor are acquired. These images are rescaled, converted to jpg format, and stored. Images in.mat format are included in the Figshare data. The data and labels from the tumour mask are rescaled, acquired, and converted to jpg format. The photos are rescaled and saved from Kaggle. The multi-label dataset is built from the processed data and labels. After then, the photos are divided into training and testing sets. Table 1 shows the class and label information.

Table 1. Multi-Task Classification data - Label information

Classification Category	Label Information
Tumor Presence	1 - No Tumor 2 - Tumor Present
Tumor Grade	1- No Grade 2- Grade 2 3- Grade 3 4 -Grade 4 5 - Unknown Grade
Tumor Type	1 - No Tumor 2 - Astrocytoma Tumor 3 - Glioblastoma Multiforme (GBM) Tumor 4 - Mixed Tumor 5 - Oligodendroglioma Tumor 6 - Meningioma Tumor 7 - Glioma Tumor 8 - Pituitary Tumor

3.3 Brain Tumor Classification Module

Because the classification entails various tasks, utilising a different model for each one is ineffective. The tumour is classified from various perspectives using the same brain MRI imaging. This classification can be thought of as a multi-task classification issue, with shared layers and individual layers for each task. The number of distinct layers varies depending on the assignment. A CNN-based multi-task classifier is included in this module. The data pre-processing module's multi-label and processed picture data are used to train this model. The test data set is then used to validate the trained model. This module indicates if a tumour is present or not, as well as the grade and kind of the tumour if it is there. The concept of multi-task categorization is derived from previous research [15],[16],[17]. Residual Network is used for CNN-based multi-task classification (ResNet34). ResNet is a CNN (Conference of Neural Networks). Figure 2 depicts this module. This model starts with shared layers containing ResNet34, then distinct layers for various brain tumour classification tasks [15]. Because there are three categorization jobs, three distinct layers were chosen.

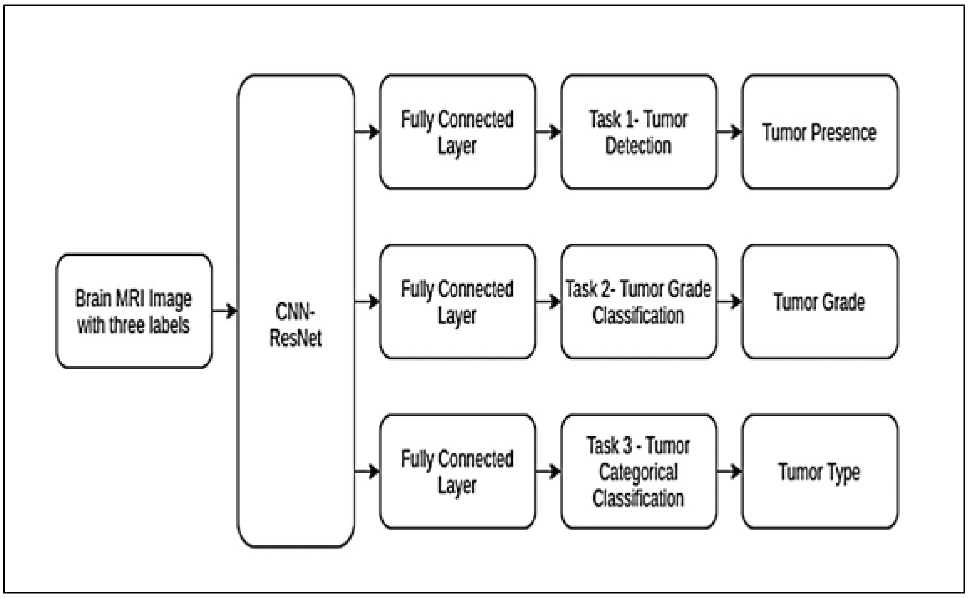

Figure 2. Architecture of Multitask Classification –Brain Tumor Classification Module

3.4 Brain Tumor Identification Module

It is critical to determine the location of a tumour in order to identify a brain tumour. The tumour can be segmented using the CNN-based UNet model. The results in [18] suggest that this paradigm is effective. This model is first trained using both image and tumour mask data. This UNet-CNN model processes the images that are detected with the tumour to segment the model's tumour [18]. As projected outcomes, this module displays the tumor's location.

IV. EXPERIMENTAL RESULTS

By adjusting parameters such as learning rate, batch, and epochs, the classification and tumour identification modules were tested. The hyperparameters with the best results were selected. The remaining 20% of the data is used to test the trained modules. Each task-specific layer of the multi-task classifier is equipped with multiple loss computations, which are eventually integrated. Figure 3 shows an example of a result obtained. The overall accuracy of this model was 92 percent. The Dice coefficient is used to evaluate the tumour identification module. An average Dice score of 0.89 is obtained. The Dice coefficient for each epoch while training the UNet –CNN

Figure 4 depicts the module. Figure 5 shows an example of a result received after using the tumour detection module.

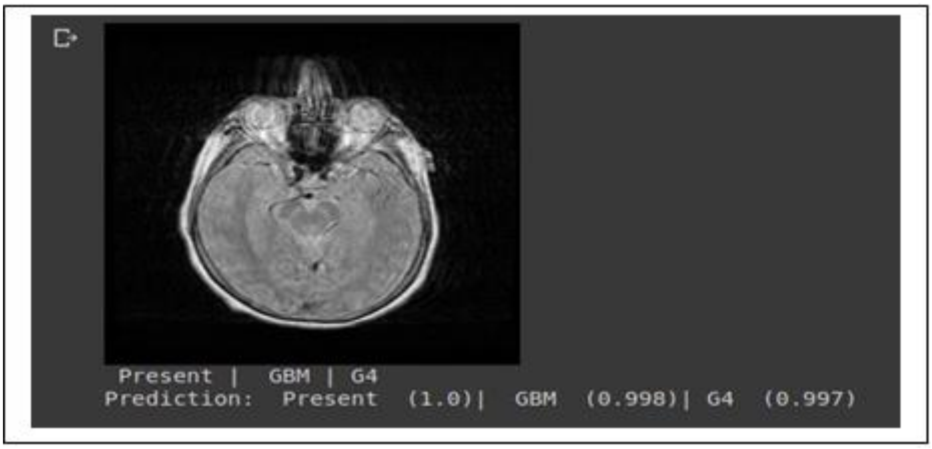

Figure 3. SampleResult of brain Tumor Classification module

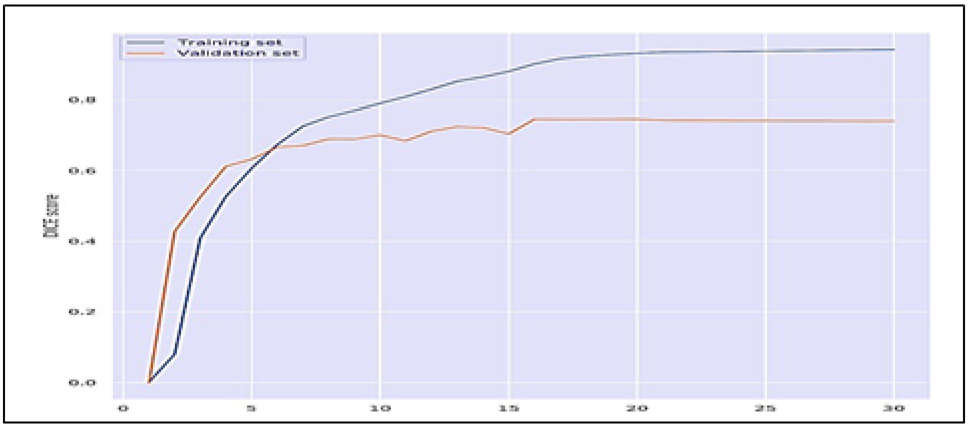

Figure 4. Brain Tumor Identification Module – Model Training DICE Score

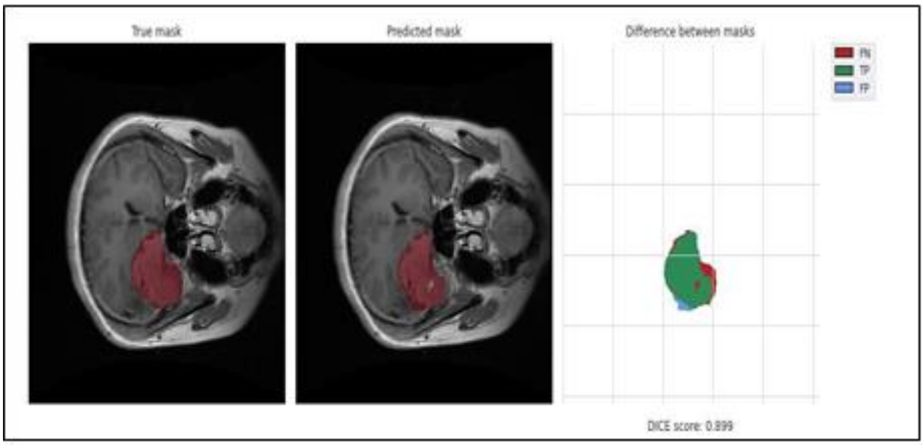

Figure 5. Sample Result of Brain Tumor Identification Module

V. CONCLUSION

Various strategies for detecting, segmenting, and classifying brain tumours have been proposed. The majority of these studies concentrate on major tumour types for classification. The lack of a database on rare tumour types is the cause behind this. We must determine whether the brain tumour is malignant or benign, as well as its location, grade, and kind, in order to diagnose and treat it. A few known methods for detection and classification use distinct models, resulting in increased computing complexity. We have proposed a method that addresses these two major concerns. The Convolutional Neural Network is used in our model. The method uses brain tumour categorization and brain tumour identification modules to gather all of the results needed to diagnosis. Rather than employing a new model for each classification, this brain tumour classification model use a multi-task classifier. This method can be used to classify unusual tumour types because the diagnosis can be made using other information.

VI.REFERENCES

[1]. T. M. Shahriar Sazzad, K. M. TanzibulAhmmed, M. U. Hoque and M. Rahman, Development of Automated Brain Tumor Identification Using MRI Images, 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), Cox'sBazar, Bangladesh, 2019, pp. 1-4, doi: 10.1109/ECACE.2019.8679240.

[2]. Shanmuga Priya S., Saran Raj S., Surendiran B., Arulmurugaselvi N. (2021) Brain Tumour De- tection in MRI Using Deep Learning. In: Bhateja V., Peng SL., Satapathy S.C., Zhang YD. (eds) Evolution in Computational Intelligence. Advances in Intelligent Systems and Computing, vol 1176. Springer, Singapore. https://doi.org/10.1007/978-981-15-5788-0_38

[3]. H. E. M. Abdalla and M. Y. Esmail, Brain Tumor Detection by using Artificial Neural Net- work,2018 International Conference on Computer, Control, Electrical, and Electronics Engi- neering (ICCCEEE), Khartoum, 2018, pp. 1-6, doi: 10.1109/ICCCEEE.2018.8515763.

[4]. S. Akbar, S. Nasim, S. Wasi and S. M. U. Zafar, Image Analysis for MRI Based Brain Tumor Detection, 2019 4th International Conference on Emerging Trends in Engineering, Sciences and Technology (ICEEST), Karachi,Pakistan, 2019, pp. 1-5, doi:10.1109/ICEEST48626.2019.8981681.

[5]. M. Gurbină, M. Lascu and D. Lascu, Tumor Detection and Classification of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines, 2019 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 2019, pp. 505-508, doi: 10.1109/TSP.2019.8769040.

[6]. P. Dvorak, W. Kropatsch and K. Bartusek, Automatic detection of brain tumors in MR images, 2013 36th International Conference on Telecommunications and Signal Processing (TSP), Rome, 2013, pp. 577-580, doi: 10.1109/TSP.2013.6614000.

[7]. Ezhilarasi, R. & Varalakshmi, P.. (2018). Tumor Detection in the Brain using Faster R-CNN. 388-392. 10.1109/I-SMAC.2018.8653705.

[8]. R. Vinoth and C. Venkatesh, Segmentation and Detection of Tumor in MRI images Using CNN and SVM Classification, 2018 Conference on Emerging Devices and Smart Systems (ICEDSS), Tiruchengode, 2018, pp. 21-25, doi: 10.1109/ICEDSS.2018.8544306.

[9]. Tarik H., Tawfik M., Youssef D., Simohammed S., Mohammed O.J., Miloud J.E. (2020) To- wards an Improved CNN Architecture for Brain Tumor Classification. In: Serrhini M., Silva C., Aljahdali S. (eds) Innovation in Information Systems and Technologies to Support Learning Re- search. EMENA-ISTL 2019. Learning and Analytics in Intelligent Systems, 7. Springer, Cham. https://doi.org/10.1007/978-3-030-36778-7_24

[10]. D. Divyamary, S. Gopika, S. Pradeeba and M. Bhuvaneswari, Brain Tumor Detection from MRI Images using Naive Classifier, 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2020, pp. 620-622, doi: 10.1109/ICACCS48705.2020.9074213.

[11]. PrakashDuraisamy, XiaohuiYuan, ElSaba,A. and Sumithra Palanisamy, Contrast enhancement and assessment of OCT images, Proceedings of International Conference on Informatics, Elec- tronics & Vision (ICIEV), 2012 Date: 18-19 May 2012 pp.91-95(Location :Dhaka, Print ISBN: 978-1-4673-1153-3,INSPEC Accession Number: 13058449,Digital Object Identifier:10.1109/ICIEV.2012.6317381)

[12]. Sumithra M. G., Thanushkodi, K. and Helan Jenifer Archana ,A. A New Speaker Recognition System with Combined Feature Extraction Techniques , Journal of Computer Science, Vol. 7, Issue 4, pp.459- 465, 2011. (With impact factor SNIP of 0.162 and SJR of0.034).

[13]. Balasaraswathi, M., Srinivasan, K., Udayakumar, L., Sivasakthiselvan, S. and Sumithra, M.G., 2020. Big data analytic of contexts and cascading tourism for smart city. Materials Today: Pro- ceedings.

[14]. Sivakumar, P., Boopathi, C.S., Sumithra, M.G., Singh, M., Malhotra, J. and Grover, A., 2020. Ultra-high capacity long-haul PDM-16-QAM-based WDM-FSO transmission system using co- herent detection and digital signal processing. Optical and Quantum Electronics, 52(11), pp.1- 18.Yoo, Byungin& Kwak, Youngjun& Kim, Youngsung& Choi, Changkyu& Kim, Junmo. (2018). Deep Facial Age Estimation Using Conditional Multitask Learning With Weak Label Expansion. IEEE Signal Processing Letters. pp 1-1. 10.1109/LSP.2018.2822241.

[15]. Das, Abhijit &Dantcheva, Antitza. (2018). Mitigating Bias in Gender, Age, and Ethnicity Clas- sification: a Multi-Task Convolution Neural Network Approach.

[16]. Alhichri, H.. Multitask Classification of Remote Sensing Scenes Using Deep Neural Networks. IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium (2018): 1195-1198

[17]. PrakashDuraisamy, XiaohuiYuan, ElSaba,A. and Sumithra Palanisamy, Contrast enhancement and assessment of OCT images, Proceedings of International Conference on Informatics, Elec- tronics & Vision (ICIEV), 2012 Date: 18-19 May 2012 pp.91-95(Location :Dhaka, Print ISBN: 978-1-4673-1153-3,INSPEC Accession Number: 13058449,Digital Object Identifier:10.1109/ICIEV.2012.6317381)

[18]. Sumithra M. G., Thanushkodi, K. and Helan Jenifer Archana ,A. A New Speaker Recognition System with Combined Feature Extraction Techniques , Journal of Computer Science, Vol. 7, Issue 4, pp.459- 465, 2011. (With impact factor SNIP of 0.162 and SJR of0.034).

[19]. Balasaraswathi, M., Srinivasan, K., Udayakumar, L., Sivasakthiselvan, S. and Sumithra, M.G., 2020. Big data analytic of contexts and cascading tourism for smart city. Materials Today: Pro- ceedings.

[20].Sivakumar, P., Boopathi, C.S., Sumithra, M.G., Singh, M., Malhotra, J. and Grover, A., 2020. Ultra-high capacity long-haul PDM-16-QAM-based WDM-FSO transmission system using co- herent detection and digital signal processing. Optical and Quantum Electronics, 52(11), pp.1- 18.Yoo, Byungin& Kwak, Youngjun& Kim, Youngsung& Choi, Changkyu& Kim, Junmo. (2018). Deep Facial Age Estimation Using Conditional Multitask Learning With Weak Label Expansion. IEEE Signal Processing Letters. pp 1-1. 10.1109/LSP.2018.2822241.

[21].Das, Abhijit &Dantcheva, Antitza. (2018). Mitigating Bias in Gender, Age, and Ethnicity Clas- sification: a Multi-Task Convolution Neural Network Approach.

[22].Alhichri, H.. Multitask Classification of Remote Sensing Scenes Using Deep Neural Networks. IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium (2018): 1195-1198.

[23].Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Im- age Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) Medical Image Com- puting and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Computer Science, 9351. Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28