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Sustainable and Reliable Healthcare Automation and Digitization using Machine Learning Techniques

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Healthcare 4.0 takes significant benefits while aligned with Industry 4.0. Mainly citing the recent and existing pandemic, the need for Industry Internet of Things (IIoT), automation, digitalization, and induction of machine learning techniques for forecasting and prediction have been the technologies to rely on. On these lines, digitization and automation in the healthcare industry have been practical tools to accelerate diagnosis and provide handy second opinions to practitioners. Sustainability in health care has several objectives, like reduced cost and low emission rate, while promising effective outcomes and ease of diagnosis. In this paper, such an attempt has been made to employ deep learning techniques to predict the phase of brain tumors. The deep learning methods help practitioners to correlate patients' status with similar subjects and assess and predict future anomalies due to brain tumors. Popular datasets have been employed for modeling the prediction process. Machine learning has been the most successful tool for handling supervised classification while dealing with complex patterns. The study aims to apply this machine learning technique to classifying images of brains with different types of tumors: meningioma, glioma, and pituitary. The simulation is performed in a python environment, and analysis is carried out using standard metrics.

Keywords: Brain tumor, Deep learning, Healthcare 4.0, Industry 4.0, Sustainable technology

Introduction

Healthcare automation is much needed to meet the challenges like remote diagnosis and medication. The advancements in medical imaging led to efficient human organ analysis, which significantly contributed to respectable and influential diagnosis and further treatment. These advanced imaging techniques have become a handy tool for radiologists. Out of several organs, the brain makes up the core part, and this organ regulates the nervous system. Brain tumor is one of the foremost common and, therefore, the deadliest brain diseases that have affected and ruined several lives worldwide. Cancer is a disease in the brain in which cancer cells ascend in brain tissues. According to a new study on cancer, more than one lakh people are diagnosed with brain tumors annually around the globe. Regardless of stable efforts to overcome the complications of brain tumors, figures show unpleasing results for tumor patients.

The diseases affecting different body organs may be limited to one organ or spread to another. However, most brain diseases impact the functioning of other organs and may put the patients in dangerous situations and lead to death.[1] So, the identification and treatment planning of brain diseases is an important task. Automating medical image diagnosis and analysis plays a vital role in treatment decisions. Analysis part of medical images is done by processing them through some image processing techniques.

Several algorithms are proposed to classify bio-medical images for effective digitalization, automation, and diagnosis. An expert system approach is presented using type-II fuzzy logic for classification. The proposed technique proved to be better in classifying brain tumors and valuable for diagnosis.[2]

The work presented in this paper corresponds to the implementation of the brain tumor classification framework using Neural Networks and machine learning techniques such that a comparative analysis can be drawn. The dataset has been downloaded from Kaggle as provided by Sartaz, and machine learning tools and libraries like Keras and sklearn are used for the simulation. The analysis is carried out using standard metrics like accuracy and loss. Brain tumor

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images are classified into four types. Besides the no-tumor case, the other three types are Glioma, meningioma, and pituitary.

Literature Survey

Classification, clustering, and modeling can be performed on the features extracted from the brain images. These are typical engineering techniques when real-world problems are translated to engineering problems. An accuracy of 89%, recall of 89%, and true negative rate of 90% are achievable using machine learning techniques to classify the type-II astrocytomas in the brain using the corresponding MRI images.[3] Similarly, the multiscale fuzzy C-means fully automatically classify brain tumors. In brief, the methodology is to employ three methods, i.e., Conventional fuzzy C-Means, Modified fuzzy C-Means and Multiscale fuzzy C-Means, and draw a performance comparison on the McGill brain dataset.[4]

Clustering can also be effectively implemented in brain tumor detection using various deterministic and non-deterministic approaches.[5] Accordingly, the Fuzzy C-means algorithm is superior to other clustering procedures employed in image segmentation.[6] Fazel *et al.* have compared the existing filtering methods based on fuzzy rule as a preprocessing step.[7] The fuzzy concepts blended with the Possibilistic C-Mean proved effective in terms of Mahalanobis distance, and Kwon validity index especially in image segmentation. Thresholding technique is used for Feature Extraction and developed Brain MRI tumor grade classification system using Type-II Approximate Reasoning method.

Feature extraction weights play a vital role in Classifier model construction in Deep learning. The pre-trained CNN models are used for feature extraction in transfer learning, and hybrid transfer learning models. The performance of the above models can be improved by fine-tuning the pre-trained model CNN layers to classify target datasets.

Tumors may be benign or malignant, appear in different brain parts, and may be categorized as either primary or secondary. A primary tumor has started in the brain, in contrast to a metastatic tumor that has spread to the brain from another region of the body.[8] The frequency of metastatic tumors is about four times higher than that of primary tumors.[9] The frequency of tumors in India ranges from 5% to 10% of the population and accounts for 2% of malignancies.[10] The most common primary tumors were astrocytomas (38.7%), with the remaining high-grade gliomas (59.5%). More importantly, during the presentation, the median age of glioma tumors was shown to be at least ten years older than recorded in the western population, which can be partly explained by lower life expectancy and a higher proportion of younger people in India.

The brain is a significant and complex organ in the nervous system. It controls movements, stores, incorporates, and coordinates the information it receives from the sense organs, and makes decisions on the commands it delivers to the rest of the organism. Brain tumors are found to be a life-threatening issue for humankind, irrespective of age and gender. A tumor is an intense cell swelling or massive cell growth that is formed by irregular brain cell development, and its manifestations shift within the brain tumor region in the protected area of the skull bone. How quickly a brain tumor can develop can differ considerably. The rate of development, as well as the location of a brain tumor, determines how it affects nervous system activity. Automatic classification and detection of tumors in distinctive restorative images was convinced when handling a human life by the need for great accuracy. The median age of pediatrics is low, which is a severe factor of concern. Another multi-institutional initiative involving seven tertiary care hospitals identified the epidemiological profile of 3936 pediatric tumor patients. Astrocytoma (34.7%) was the most common tumor followed by MB, supratentorial PNETs (22.4%), and craniopharyngioma. Many astrocytic tumors were confirmed to be low-grade, typically pilocytic astrocytoma and astrocytoma of subependymal giant cells. It was comparable with data from west or other Asian countries. The medical image analysis and preparation in this situation significantly affect non-intrusive diagnosis and clinical consideration.[11] It also provides specialists with new tools and methods to examine the peculiarities in the collected patient pictures. Specialists can have a point-by-point, unambiguous internal brain structure and differentiate between variations. It is known from this technique that earlier tumor identification and diagnosis help save lives. Therefore, getting a computer-aided diagnostic system is essential for doctors to recognize the various tumor classes and the extent of the specific tumor.

As it involves life-saving, developing a deep learning-based classifier is essential to classify the tumor class using the MRI. Hence it needs to train the classifier with many MRI dataset from different resources to advance the accuracy and reduce the detection of faults in the diagnosis process.

Materials and Methods

Brain Tumour

A brain tumor is an irregular mass of tissue in which cells grow and multiply uncontrollably, seemingly uncontrolled by the mechanisms that govern normal cells. The brain is encapsulated with a hard-core called skull is very rigid, and any growth of abnormal cells causes a problem in such a restricted space. Brain tumors can be cancerous (malignant) or noncancerous (benign), and they can increase the pressure within the skull as benign or malignant tumors develop.

This can cause damage to the brain, which may be life-threatening, and 2% of cancers are brain tumors.[3] There are over 150 types of tumors in the brain. According to the world health organization, brain tumors are categorized into four classes, Grades I, II, III and IV.[6] The grading of the tumors is done based on their attributes. Grade-I and Grade-II are tumors of low grade, and tumors of high are Grade-III and Grade-IV.

Glioma is a tumor located in the brain or spine glial cells.[7] About 30% of all brain tumors are gliomas, while 80% of all brain cancers.[8] The gliomas of high grade can be seen in Fig. 1(a). Low-grade gliomas are considered benign tumors, and high-grade gliomas are considered malignant tumors.

Meningioma is a tumor that develops on membranes that cover the brain and the spinal cord within the skull.[9] These are slower-growing intracranial tumors, and 90% of them are benign. The meningioma brain tumor can be seen in Fig. 1(c). Pituitary adenomas are the most common intracranial tumors, including gliomas and meningiomas. The Pituitary brain tumor can be seen from Fig. 1(b). The vast majority of pituitary adenomas are benign, and fairly slow-growing, and about 35% are invasive, with just 0.1% to 0.2% being carcinomas.[10]

CNN - Convolutional Neural Networks

Convolution is considered as a significant concept in CNN. The filter employed will be responsible for the convolution phase between the local pixels in close proximity.[12,13] This step subsequently

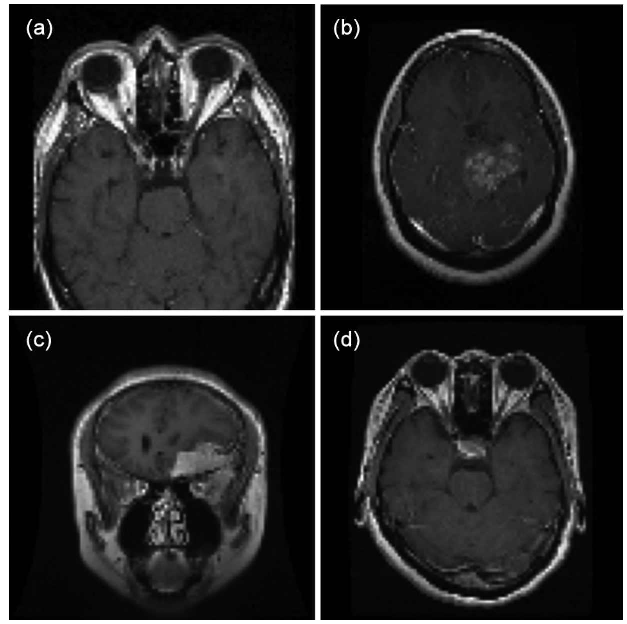

Fig. 1 — Sample MRI images of brain with (a) No tumor, (b) Glioma, (c) Meningioma, and (d) Pituitary

systematically runs through the entire image to cover the whole picture. This is given as Eq. 1

$$S(m,n) = \sum_{i,j=-q}^{q} x(m-i,n-j)w(i,j) \qquad \ldots (1)$$

Here, w (I, j) is the filter generated by the network. Usually, each layer performs more than one convolution with different filters to obtain multiple convolution images from a single input image. Accordingly, it is possible to differentiate them into three broad layers. The first is the Convolutional layer which is used to transform an input volume into a volume of features given by convolutions of the initial one. Another layer is referred as the activation layer in which every single component is passed within an activation function like tanh, and sigmoid etc. the final is the max pooling layer which involves in dimensional reduction considering a certain region of features. This can take its average or the minimum value or the maximum value or functions of these.

At the end of these layers, the features are "flattened" and passed inside a Feed Forward neural network, at the end are the four forecast layers. Each of the four forecasts is one of the four classification types in our problem.

Random Forest Classification Method

A Random Forest is well-suited for classification problems. It typically combines the result of several Decision Trees. Hence there is a noticeable improvement in the prediction accuracy. A Decision

Tree algorithm relies on binary decisions. In each node, the dataset is divided into two parts. This process of division is continuous using the binary decision. This eventually classified in a certain way.

In this work, the scikit – learn library is extensively used to implement the python code for RFC. Several classification metrics like precision, recall, F1-score, accuracy, and confusion matrix help evaluate the classification model. However, the confusion matrix and the loss/accuracy are considered in the present work. Typically, the confusion matrix helps count the number of samples right or wrong for every class. Accordingly, it frames out a matrix mapping True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN). The correct and correctly predicted samples are treated as TP, while those mispredicted are FP. Conversely, it is possible to realize the concept of FN and TN. Further, the other parameter, accuracy, is defined as in following Eq. 2

$$Accuracy\ (A) = \frac{Number\ of\ TP}{Total\ number\ of\ predictions} \quad \ldots (2)$$

Here, the benchmark value of 'A'varies with the type of classification problem. It is widely accepted to consider an 80% or above accuracy as a good model.

Results and Discussion

The dataset used contains images obtained through MRI of healthy brains and brains affected by one of the three types of tumors. The manually assigned labels to these images are considered for the simulation. The dataset has 3264 images in total. The sample images from the dataset are given in Fig. 1. These are into two parts proportionately for Testing and Training as 80% and 20%, respectively. The images in the dataset are of different dimensions and require preprocessing to bring them to a uniform size.

The work employs two machine-learning techniques to frame a prediction model to classify the images. The two techniques are random forest and CNN, and this can subsequently compare and suggest the best suitable ML method for categorizing the brain MRI data. Efforts are taken to avoid biasing in the classification types regarding the number of images per type, and a uniform count is maintained for this purpose. However, the "no tumor" case is exceptional, with fewer images. Further, following the manual labeling process, the data were combined during the training and testing to avoid biasing. Hence, the data has been randomly chosen for training and testing, irrespective of the category.

The CNN typically receives input images of the dataset suitably resized to a uniform dimension. Similarly, the RF has images as input without any filter. The performance can be evaluated in terms of accuracies computed over the training and testing phases.

The simulation of the implementation of CNN with 20 epochs is performed and the corresponding accuracy and loss are computed in every epoch through both training and testing phases. The accuracy is plotted in Fig. 2 where the performance in training and testing phases can be studied.

The predicted images in the training phase are presented in Fig 3. The predicted glaucoma images are given in Fig. 3(a–d). Similarly predicted images of pituitary, meningioma and Non-tumor images are presented in Fig. 3(e–h), Fig. 3(i–l) and Fig. 3(m, n), respectively.

About 80% of the data has been used for training purpose while the rest 20% is reserved for testing. Following the training phase, the developed model has been tested with the reserved images. An accuracy of 100% is an ideal case, however in practice, the value of accuracy is less than 100% and as a result, in testing phase some predictions are wrong.

Accordingly, the results pertaining to the predictions in testing phase are presented in Fig. 4(a) through Fig. 4(l). The Figs 4(a, b, e, g & h) are predicted as glioma. However, the data set clearly identifies that, Fig. 4(b) and Fig. 4(g) have no tumor while they are wrongly predicted as Glioma. Similarly referring to the remaining figures, it is possible to

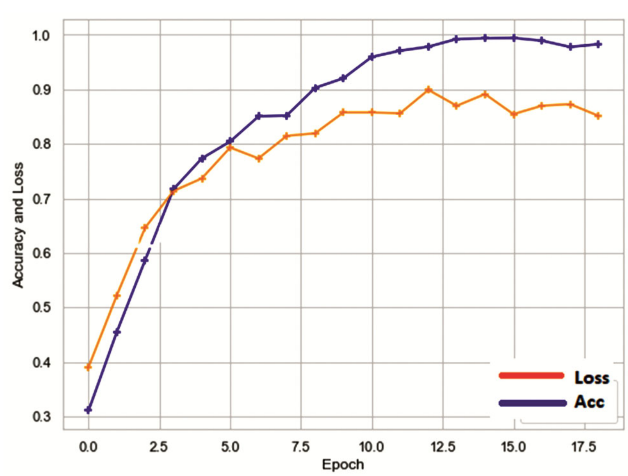

Fig. 2 — Accuracy evaluation for Training and Testing phases

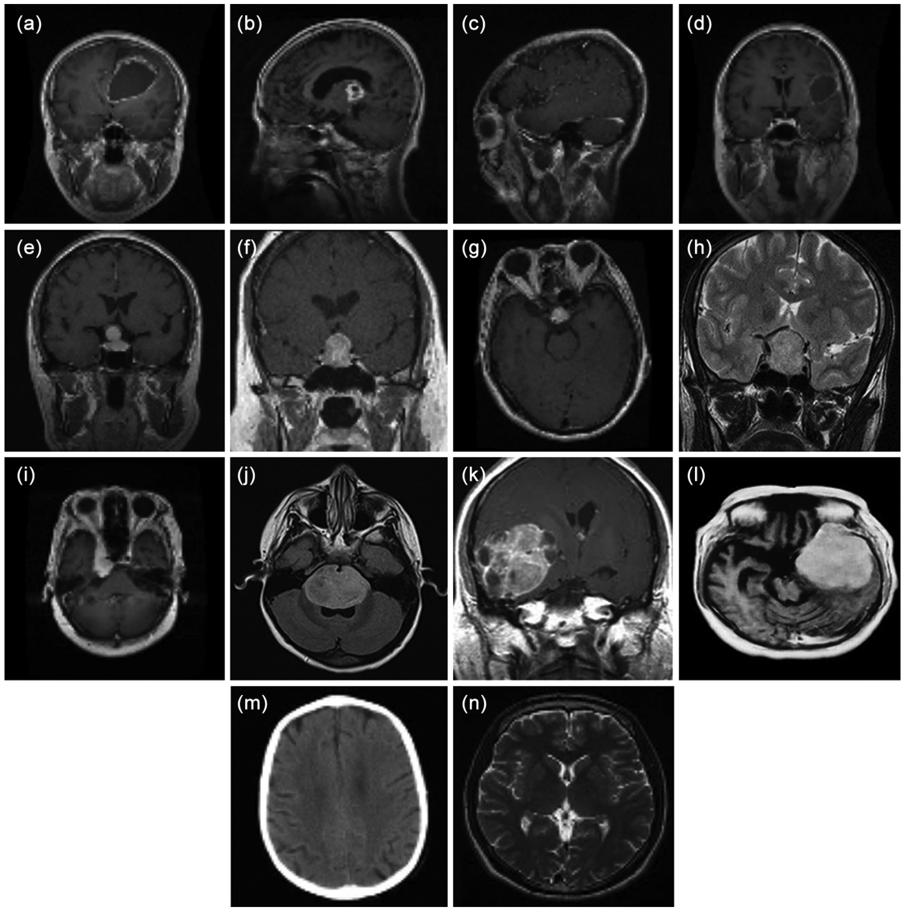

Fig. 3— Prediction during the Training phase for (a-d) Glioma, (e-h) Pituitory, (i-l) Maningioma and (m,n) no tumor

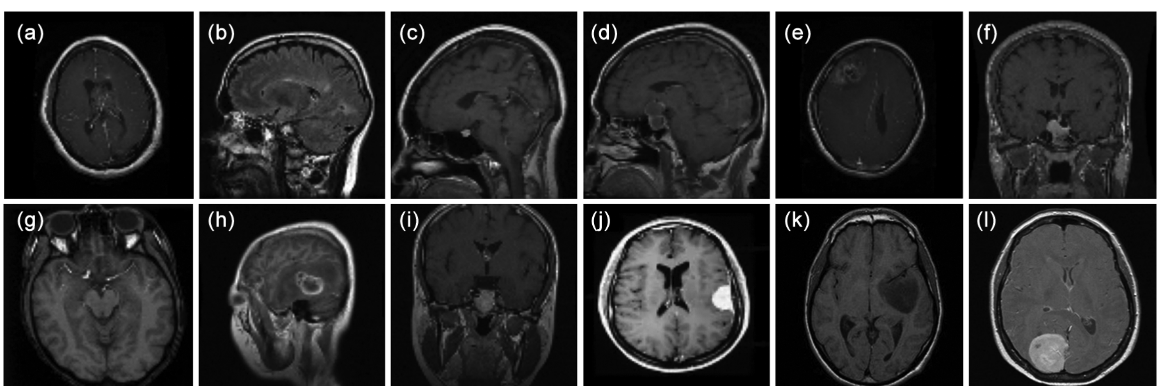

Fig. 4 — Prediction during the Testing phase (a) gioma predicated as Glioma, (b) no tumor predicted as Glioma, (c) pituitary predicted as pituitary, (d) pituitary predicted as pituitary, (e) gioma predicated as Glioma, (f) pituitary predicted as pituitary, (g) no tumor predicted as Glioma, (h) gioma predicated as Glioma, (i) pituitary predicted as pituitary, (j) meningioma predicted as meningioma, (k) no tumor predicted as no tumor, and (l) meningioma predicted as meningioma

mention that they are rightly predicted. The accuracy are loss in training and testing phases is recorded in Table 1.

Table 1 — Accuracy and loss of the best CNN model

Phase	Accuracy	Loss
Training	0.983	0.1287
Testing	0.851	0.5660

RF Method

In the RF technique, the parameters like the number of trees and depth are significant, and performance enhances with a large number of trees with a certain depth. However, performance does not improve beyond a certain value of depth and a certain

Table 2 —Accuracy values (Training; Testing)

Depth	5	10	20	50	100	200	500
5	0.77; 0.73	0.81; 0.77	0.8; 0.74	0.81; 0.75	0.82; 0.75	0.81; 0.76	0.81; 0.74
10	0.96; 0.84	0.98; 0.84	0.98; 0.85	0.99; 0.88	0.99; 0.88	0.99; 0.87	0.99; 0.88
15	0.98; 0.82	0.99; 0.86	1.0; 0.86	1.0; 0.88	1.0; 0.87	1.0; 0.88	1.0; 0.88
20	0.98; 0.83	1.0; 0.86	1.0; 0.87	1.0; 0.87	1.0; 0.87	1.0; 0.89	1.0; 0.88
25	0.98; 0.84	1.0; 0.85	1.0; 0.86	1.0; 0.87	1.0; 0.88	1.0; 0.89	1.0; 0.89
30	0.99; 0.82	1.0; 0.85	1.0; 0.87	1.0; 0.87	1.0; 0.88	1.0; 0.88	1.0; 0.89

Number of trees

Table 3 — Confusion Matrix

	Glioma	Pituitary	Meningioma	No Tumor
Glioma	151	0	4	0
Pituitary	3	156	12	2
Meningioma	24	1	170	18
No Tumor	11	0	11	90

number of trees within the Random Forest. Hence a proper choice of these parameters is necessary. In the current work a Random Forest with 100 decision trees is considered, with a maximum depth of 15 levels. Each Decision Tree is trained on a different portion of the dataset. The classification and regression tree algorithm for dividing the two regions at each node selects the two areas to minimize the function. The training and testing accuracy values are given in Table 2 respectively. A maximum accuracy of 89% is recorded in the testing phase. The corresponding confusion matrix is shown in Table 3. From the matrix, it is evident that no tumor sees mere chances of getting predicted as Glioma, with meningioma as no tumor.

Conclusions

Application of Machine learning techniues is a way to achieve sustained health care through automation and techniques of handling large volumes of data in terms of medical reports and performing analysis. This paper accomplished the task of adopting machine learning techniques for brain tumor classification and analysis with four categories namely glioma, pituitary, meningioma and no tumor as outputs. The CNN and the RF are effectively implemented and the performance is evaluated in terms of accuracy and loss metrics. Few observations are derived from the analysis in which the first observation concludes that the CNN is a better option than the RF in terms of computational time and complexity. Further, as a second observation it is clear that the glioma has a close match with the no tumour and hence often mispredicted for each other. Implementation of this approach in realtime with interactive cloud computing can enhance the pace and automation process and can be a good scope of future work.

References

1 Dawe R J, Yu L, Schneider J A, Arfanakis K, Bennett D A & Boyle P A, Postmortem brain MRI is related to cognitive decline, independent of cerebral vessel disease in older adults, *Neurobiol Aging*, **69** (2018) 177–184.

2 Xiao Y, Fonov V, Chakravarty M M, Beriault S, Al Subaie F, Sadikot A, Pike G B, Bertrand G & Collins D L, A dataset of multi-contrast populationaveraged brain MRI atlases of a Parkinson ' s disease cohort, *Data Brief*, **12** (2017) 370–379.

3 Zarinbal M, Fazel Zarandi M H, Turksen I B & Izadi M, A type-2 fuzzy image processing expert system for diagnosing brain tumors, *J Med Syst*, **39** (2015) 110.

4 Wang H & Fei B, A modified fuzzy C-means classification method using a multiscale diffusion filtering scheme, *Med Image Anal*, **13** (2019) 193–202.

5 Patel S A & Shah U V, Tumor location and size identification in brain tissues using Fuzzy C- clustering and artificial bee colony algorithm, *Int J Eng Dev Res*, **2** (2014) 3131–3134.

6 Shanthakumar P & Ganeshkumar P, Performance analysis of classifier for brain tumor detection and diagnosis, *Comput Electr Eng*, **45** (2015) 302–311.

7 Zarandi M F, Zarinbal M & Izadi M, Systematic image processing for diagnosing brain tumors: A Type-II fuzzy expert system approach, *Appl Soft Comput*, **11** (2011) 285–294.

8 Anil Kumar B & Rajesh Kumar P, Multi brain tumor classification in MR brain images through transfer learning model, *J Appl Sci Comput*, **7** (2020) 41–49.

9 Anilkumar B & Rajesh Kumar P, Multi tumor classification in MR brain images through deep feature extraction using CNN and supervised classifier, *Int J Emerg Technol*, **11** (2020) 83–90.

10 Brindha P G, Kavinraj M, Manivasakam P & Prasanth P, Brain tumor detection from MRI images using deep learning techniques, *InIOP Conf Series: Mater Sci Eng*, **1055(1)** (2021) 012115.

11 Sekhar B V, Udayaraju P, Kumar N U, Sinduri K B, Ramakrishna B, Babu B S & Srinivas M S, Artificial neural network-based secured communication strategy for vehicular ad hoc network, *Soft Comput*, **13** (2022) 1–3.

12 Sekhar B V, Reddy P P & Varma G P, Performance of secure and robust watermarking using evolutionary computing technique, *J Glob inf manag*, **25(4)** (2017) 61–79.

13 Sekhar B V, Reddy P P & Varma G P, novel technique of image denoising using adaptive haar wavelet transformation, *Int Review Comp Soft*, **10(10)** (2015) 1012–1017.