ADVANCED LOGISTIC REGRESSION FOR DETECTING THE BRAIN TUMOUR CELLS

KOWSHIKA A [1*] SHOBANA M [2] KAVITHA M S [3]

[1*] Professor, Department of Computer Science & Engineering,
SNS College of Engineering, Coimbatore-641107, TamilNadu, India
E-Mail: shika2906@gmail.com

[2] Assistant Professor, Department of Computer Science & Engineering,
SNS College of Technology, Coimbatore-641035, TamilNadu, India
E-Mail: shobanavsm@gmail.com

[3] Associate Professor, Department of Computer Science & Engineering,
SNS College of Technology, Coimbatore-641035, TamilNadu, India
E-Mail: drmskavitha@yahoo.com

Abstract

A single person's brain MRI scan will often include many slices spanning the 3D anatomical image. Accordingly, brain tumour segmentation from MR images is a difficult and time-consuming manual process. Additionally, avoiding biopsy and facilitating a more secure diagnosis, automated brain tumour categorization using an MRI scan is non-invasive. Researchers have put in a lot of time and energy since the turn of the millennium and the late '90s to develop a system for automatically segmenting and classifying brain tumours. Therefore, there is a wealth of literature on the topic, much of it devoted to various approaches to segmentation such as region growth, conventional machine learning, and deep learning. In a similar vein, other tasks involving brain tumour classification by histological type have been carried out, with outstanding performance outcomes produced. Noise is removed and colour is removed from the MRI pictures before they are converted to grayscale. Finally, a logistic regression is utilised for determining the types for testing images, with a success rate of 98%. This proposed scheme is provided for getting the stroke and tumour cells in details without any noise.

Keywords –.Logistic Regression, Machine Learning, Artificial intelligence, Two Models, True positive
DOINumber:10.14704/nq.2022.20.8.NQ44929 **NeuroQuantology 2022; 20(8): 9090-9098**

1. Introduction

Although machine learning has been used in a variety of industries, the vast majority of research indicates that it has been put to use in the agricultural and medical sectors for the purpose of disease detection, prediction, and categorization. Biopsy, which entails excision and pathological investigation by multiple cellular (histologic) diagnostic methods, is the gold standard for diagnosing brain tumours. However, a biopsy is an intrusive diagnostic procedure that may cause bleeding and sometimes even harm severe enough to compromise function [1]. Therefore, magnetic resonance imaging (MRI) has become the gold standard in contemporary neuroimaging for the non-invasive diagnosis of brain tumours, allowing doctors to define the tumour's anatomical, molecular, metabolic, and functional features[2].

Tumours are masses of tissue formed by the proliferation of cancer cells. Normally, cells in the body will die and be replaced by new ones. Cancerous and other tumours interfere with this phase to a lesser extent. Tumour cells proliferate despite the fact that the body has no need for them, and they do not undergo normal cell death. In this way, new cancer cells are constantly being added to the expanding tumour. A glioma is a primary brain tumour that grows and spreads very quickly. The glial tissue, from which gliomas arise, provides support and assistance to the neurons that carry information from the brain to the rest of the body. Benign and malignant brain tumours exist (cancerous). Benign tumours, also known as non-cancerous tumours, do not spread to other parts of the body. They are easily expungable and will not return. Although benign brain tumours don't spread to other parts of the body, they nevertheless inflict excruciating agony, permanent brain damage [3], and even death. The boundaries of malignant brain tumours are not well defined. They multiply rapidly, raising intracranial pressure, and may spread beyond their initial sites in the brain or spinal cord. Malignant brain tumours almost seldom metastasize to other parts of the body.

The study found that brain tumours are the leading cause of mortality throughout the globe. Hormonal shifts, blood clots, fatigue, unsteady gait, jumbled speech, emotional swings, visual problems, and more may all be indicators of something more serious. Tumours are classified according to their locations, and an accurate diagnosis might mean the difference between life and death. Cancerous tumours [4] may spread to nearby healthy tissue, whereas benign tumours cannot. You can get rid of them entirely, and they won't come back. Although benign brain tumours don't spread to other parts of the body, they nevertheless inflict excruciating agony, permanent brain damage, and even death. The boundaries of malignant brain tumours are not well defined. They multiply rapidly, raising intracranial pressure, and may spread beyond their initial sites in the brain or spinal cord. Malignant brain tumours almost seldom metastasize to other parts of the body. Many researchers have developed many ways for detecting brain tumours using MRI brain scans, however these technologies are mostly ineffective and hopelessly antiquated. A machine intelligence system is required to overcome the constraints of the prior models. MRI scans are taken in real time to evaluate subjects of varying ages and orientations. Logistic regression and threshold segmentation were used to the medical diagnosis categorization.

2. Related Works

It is hard to grasp the manifestation of a brain tumour because of the wide range of possible sizes, locations, rates of development, and pathologies. A brain tumour is an abnormal growth of tissue caused by the uncontrolled division of certain types of cells [5] – [8]. A number of mechanisms, including increased intracranial pressure, brain movement, skull compression, and nerve and healthy brain tissue invasion, have been implicated. Brain tumours may be categorised in several ways depending on the criteria employed [9] – [10]. The spinning protons are then pushed out of their stable equilibrium position by introducing a radio frequency pulse. When a radio pulse stops, the protons settle back into their original configuration and emit a sinusoidal signal whose frequency is proportional. The scanner's internal radio antenna then picks up this sinusoidal signal and converts it into a picture. Tissues differ in their signal strength depending on factors including the quantity of freely moving hydrogen protons, the velocity at which they are travelling, and the length of time [11] – [13] required for the protons to revert to their unmagnetized form inside the tissue.

However, brain tumours may be more broadly classified by their site of origin into primary and secondary (metastatic) tumours. Primary brain cancers develop from normal brain cells and are therefore categorised according to their cell of origin. Primary tumours have the potential to be both benign and malignant (cancerous) [14]. The growth of benign tumours is usually gradual, and they

never metastasize or infect nearby healthy tissue. However, they may cause the brain to experience pressure and become impaired. Instead, the malignant tumours grow fast and metastasize to other organs and tissues. Whereas primary brain tumours develop from inside the brain itself, secondary cancers spread from another organ. Primary causes of these tumours are cancer cells that originated in another part of the body and metastasized to the brain. Lung cancer, breast cancer, melanoma, kidney cancer, bladder cancer, certain sarcomas, and testicular and germ cell tumours are the leading sources of secondary brain tumours. The radiological and biochemical features of each of these tumours are distinctive [15]. Out of all survey, we have discussed and pointed the various gray area. Proposed Logistic regression was used to give good accuracy in image on comparing with existing area.

3. Methodology

Digital image processing has been used to propose a more accurate model for detecting strokes in the human brain using M R I pictures. Flow chart of the suggested model. Seven sequential phases make up the suggested detection procedure. Acquiring an MRI scan, pre-processing the scan, using the HSV colour threshold, converting the HSV scan to a binary picture, extracting features from the binary image, and finally applying a logistic regression classifier are the several stages involved.

3.1. *Acquisition*

The initial stage in any digital image processing system is called "image acquisition," and it entails taking a snapshot of an item or real scene. Radiologists have the option of employing either MRI or CT to get a picture of the brain. It is a technique used for medicine that creates high-resolution pictures of the structures and tissues deep inside a human body by combining powerful magnetic fields with radio waves. Employs a series of cross-sectional X-ray measurements to build a picture of internal organs, bones, and tissues.

3.2. Segmentation of Brain Images

Once the MRI stroke grayscale pictures have been preprocessed, a colour threshold based on the HSV hue, saturation, and value (HSV) scale is used to isolate the stroked areas of the brain. Grayscale MRI scans of the brain may benefit from this technique since it allows for the removal of any extraneous information that falls within a predetermined colour range. Finding things with dominating colour values is facilitated as well. When analysing MRI stroke pictures for stroke detection and segmentation, the HSV colour space is used as an indication of hue, saturation, and brightness within a predetermined range. Using HSV colour space, a section of the brain is divided into stroke and non-stroke areas. As shown in Architecture part that is Figure 1.

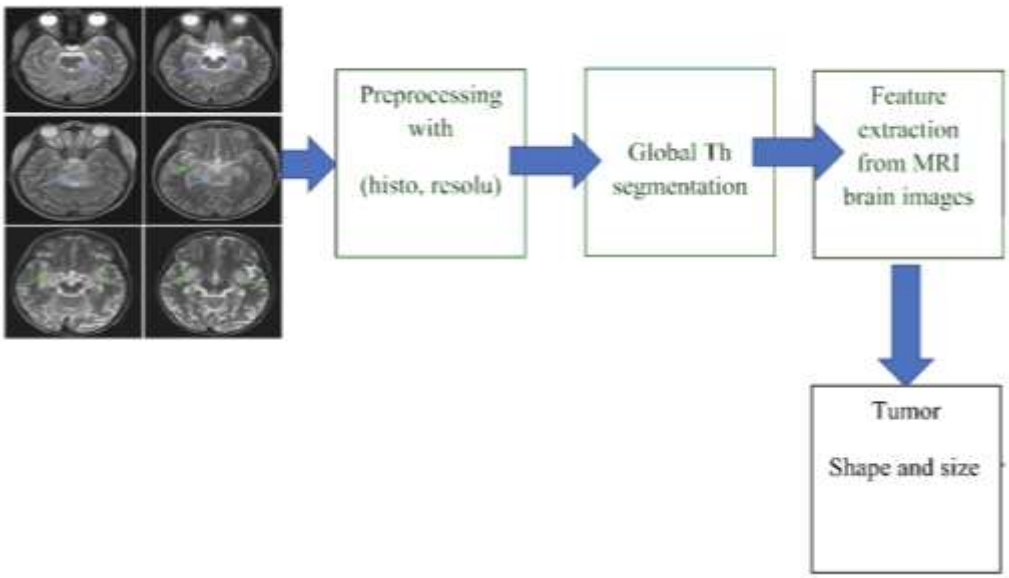

Figure 1. Workflow of Advanced Logistic Regression

Algorithm:

Input: 19 images of Brain Tumour data

Set: Dataset values to Regression

Gaussian Performance

If Test is OK then

Pre-processing and classification starts

else

Test again

Value Comparison

elif Accuracy Value

end if

Performing the segmented brain Tumour

Output: Detected Tumour Cell Images as Expected

3.3. Extraction of Images

Features extraction is the process of selecting features or properties that aid detection in image processing. It does this by constructing derived values, or features, that are meant to be non- redundant and informative, hence decreasing the dimensionality of the data. Stroke detection in this study is accomplished by the extraction of characteristics from MRI scans. Stroke characteristics have been determined for the MRI images, including the average colour. An image's dispersion or variation may be quantified with the use of a statistic called the standard deviation. When a brain stroke is detected, it is made easier when there is less variance between neighbouring pixels in a picture. Mean variance is used to quantify the degree to which a sample of randomly selected pixels deviates from the average pixel value. It's used to calculate an approximate figure for the number of stroke pixels in question. When it comes to identifying a stroke in the brain, the afflicted region is crucial. Stroke severity, such as whether it was caused by ischemia or a "mini-stroke," may be gauged by the size of the afflicted region. Because of this, MRI segmented pictures have been used to determine the extent of the damage. Stroke-related MRI scans will have a specific numerical value. MRI scans devoid of any evidence of a stroke, however, will have an essentially null numerical value. Quantitative analysis of extracted characteristics from MRI images of stroke. Herre stroke is also the big reason for tumor. Here we analysing also the stroke part to clarify the tumor cells before it yet to start. As we shown in Algorithm part.

4. Performance Evaluation

In this study, we classified stroke patients and control cases using a popular machine called the logistic regression classifier. It's also worth noting that validation was used for getting this conclusion. This conclusion is derived through analysing a confusion matrix. Sixty-one percent and change of all MRI pictures are utilised in the training process. As we can see figure 2 is prediction model 1 achievement.

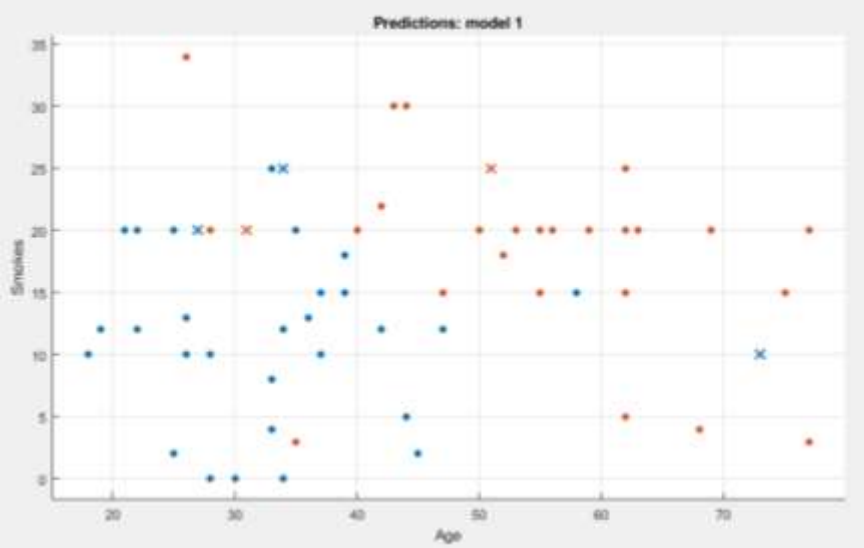

Figure 2. Prediction model 1

For the sample data used in training, the accuracy is 98.2%, the sensitivity is 100%, and the specificity is 95%. In order to ensure that our suggested model for detecting brain strokes is accurate, we utilise the remaining 37.6% of MRI pictures as a test dataset. The proposed human ischemic brain stroke detection model achieves 98% accuracy, and 100% specificity on the validation dataset. More images were taken to guarantee optimal accuracy, sensitivity, and specificity. Once we have collected all 10 readings, we can calculate the mean, which leads to better outcomes from the suggested system. Figure 3, Figure 4 and Figure 5 shows the true positive and false negative values on image data and rate values are described.

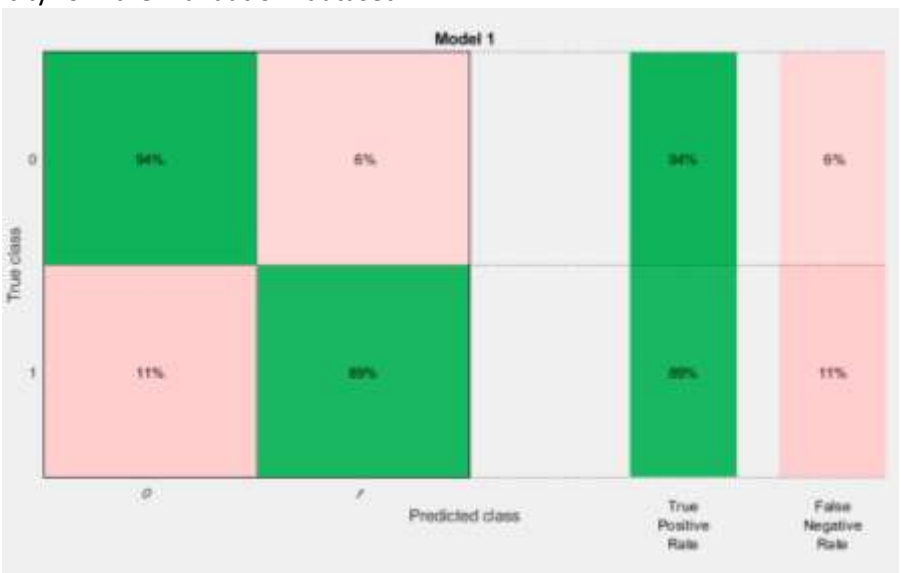

Figure 3. TP and FN of model 1

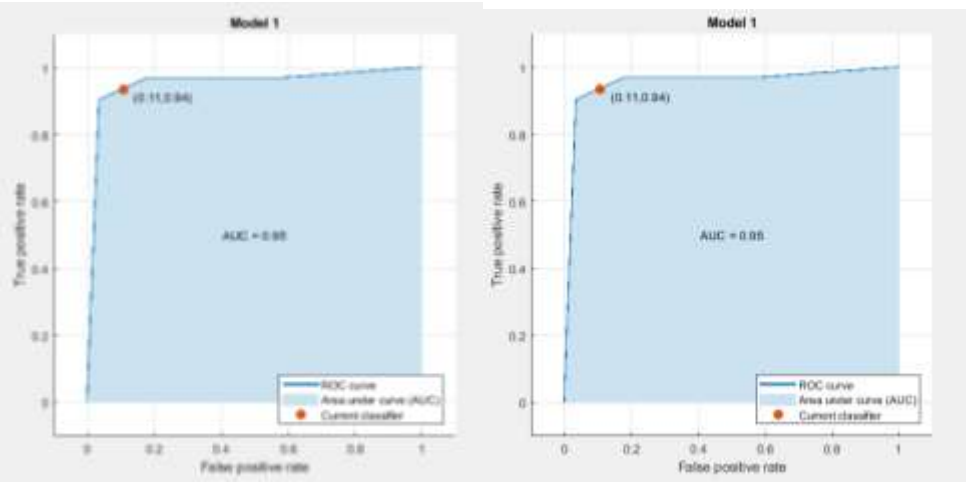

Figure 4. True positive rate of model 1

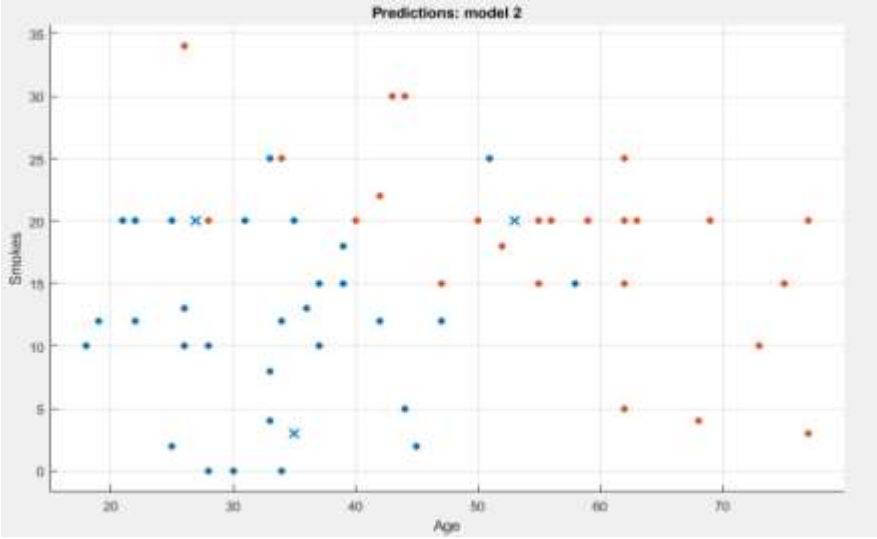

Figure 5. Prediction Model 2

It's applicable to any multinomial, ordinal, or binomial needs. Several applications in pattern recognition and the statistical sciences are possible with the help of a logistic regression classifier. The categorization relies on the four properties of the measurement variables highlighted above. The result was obtained using the 5-fold cross validation method in this study. Images of brain strokes and non-strokes are correctly recognised after data categorization. Model 2 representation was described clearly on figure 6 and figure 7.

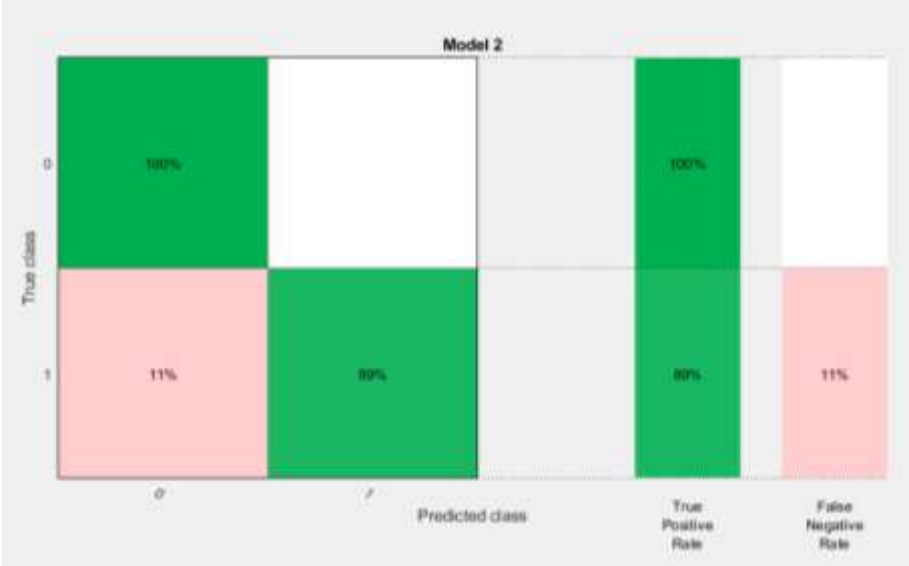

Figure 6. TP and FN model 2

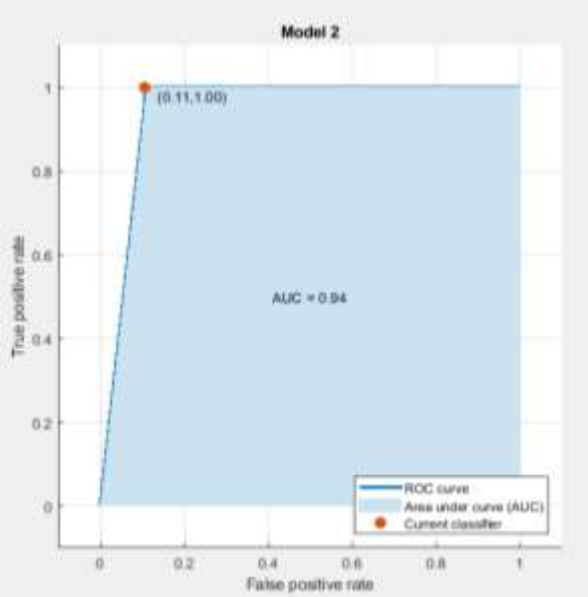

Figure 7. True Positive rate for model 2

5. Conclusion

Proposed system presented a model for detecting ischemic strokes in the human brain using logistic regression method. It is used in previous model for detecting the images in accurate value. So many models are using this concept to derive the area in detail but it seems tough in extracting the area. But this proposed model was achieved the accuracy value in best. The segmented stroke section of the MRI images has then been transformed into binary pictures to minimise the size of the calculations and extract four characteristics. The suggested system's performance is improved by the use of 5-fold cross validation to get a conclusion or outcome. When compared to previous published research, the projected performance characteristics of the proposed detection system are quite promising. Proposed scheme was achieving the best accuracy valu of 98% for detecting the tumour and stroke area in the brain. It was compared with existing scheme. in future, we can test this scheme with more than 2 models and achieve the wide area as per the needs in medical region also it can be used in the

engineering field for recognising the particular area in the given images.

References

[1]. Gajula, S., & Rajesh, V. (2022). An MRI brain tumour detection using logistic regression-based machine learning model. *International Journal of System Assurance Engineering and Management*, 1-11.

[2]. Wu, Y., Ren, P., Chen, R., Xu, H., Xu, J., Zeng, L., ... & Liu, X. (2022). Detection of functional and structural brain alterations in female schizophrenia using elastic net logistic regression. *Brain imaging and behavior*, *16*(1), 281-290.

[3]. Li, Y., Chen, B., Shi, Y., Yoshimura, N., & Koike, Y. (2022). Correntropy-Based Logistic Regression with Automatic Relevance Determination for Robust Sparse Brain Activity Decoding. *arXiv preprint arXiv:2207.09693*.

[4]. Tjerkaski, J., Nyström, H., Raj, R., Lindblad, C., Bellander, B. M., Nelson, D. W., & Thelin, E. P. (2022). Extended analysis of axonal injuries detected using magnetic resonance imaging in critically ill traumatic brain injury patients. *Journal of neurotrauma*, *39*(1-2), 58-66.

[5]. Vishal, V. V. S., Kothapalli, M. S., Sai, C. M. K., Punna, A., & Rachapudi, V. (2022, January). A Novel Survey on Copious Machine Learning Algorithms for Brain Tumor Detection. In *2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 820-826). IEEE.

[6]. Sun, C., & Holcman, D. (2022). Combining transient statistical markers from the EEG signal to predict brain sensitivity to general anesthesia. *Biomedical Signal Processing and Control*, *77*, 103713.

[7]. Chen, M., Li, Z., Yan, Z., Ge, S., Zhang, Y., Yang, H., ... & Qu, Y. (2022). Predicting neurological deterioration after moderate traumatic brain injury: development and validation of a prediction model based on data collected on admission. *Journal of neurotrauma*, *39*(5-6), 371-378.

[8]. Kwon, H., & Lee, S. (2022). Friend-guard adversarial noise designed for electroencephalogram-based brain–computer interface spellers. *Neurocomputing*, *506*, 184-195.

[9]. Dimitri, G. M., Beqiri, E., Placek, M. M., Czosnyka, M., Stocchetti, N., Ercole, A., ... & Lió, P. (2022). Modeling brain–heart crosstalk information in patients with traumatic brain injury. *Neurocritical Care*, *36*(3), 738-750.

[10]. Woldeyohannes, G. T., & Pati, S. P. (2022). Brain MRI Classification for Detection of Brain Tumors Using Hybrid Feature Extraction and SVM. In *Intelligent and Cloud Computing* (pp. 571-579). Springer, Singapore.

[11]. Sørensen, P. T., Nyborg, G., Lorentsen, T., Olasveengen, T. M., Langerud, A. K., Aarhus, M., ... & Netteland, D. F. (2022). Vasospasm Surveillance by a Simplified Transcranial Doppler Protocol in Traumatic Brain Injury. *World Neurosurgery*.

[12]. Abou Khalil, E., Gaines, B. A., Kellogg, R. G., Simon, D. W., Morgan, K. M., Richardson, W. M., & Leeper, C. M. (2022). Association of Thromboelastography with Progression of Hemorrhagic Injury in Children with Traumatic Brain Injury. *Neurocritical Care*, 1-9.

[13]. Wei, S., Liu, W., Xu, M., Qin, H., Liu, C., Zhang, R., ... & Wang, Q. (2022). Cathepsin F and Fibulin-1 as novel diagnostic biomarkers for brain metastasis of non-small cell lung cancer. *British Journal of Cancer*, 1-11.

[14]. Thompson, E., Banerjee, S., Thompson, S., Silva, R., Muse, A., Arif-Tiwari, H., ... & Nfonsam, V. (2022). Incidence and predictors of brain metastasis in colorectal cancer patients. *International Journal of Colorectal Disease*, *37*(1), 153-159.

*e*ISSN1303-5150

[15]. Harreld, J. H., Khan, A., Angel, J., Han, Y., Li, Y., Gajjar, A., & Patay, Z. (2022). MRI sequences and interslice gap influence leptomeningeal metastasis detection in children with brain tumors. *Neuroradiology*, 1-10.