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A Systematic Review on Brain Tumor Detection Using Machine Learning

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Abstract- Brain tumors are one of the deadliest forms of cancer, and early detection is critical for improving patient outcomes. Although several large initiatives and findings in this sector, proper segmentation and categorization remain difficult tasks. This proposed systematic review aimed to evaluate the current state of the field of ML for brain tumor detection and to identify areas for future research. A comprehensive search of multiple databases was conducted to identify relevant studies. This systematic review aimed to evaluate the current state of the field of ML for brain tumor detection and to identify areas for future research. A comprehensive search of multiple databases was conducted to identify relevant studies. The included studies were critically appraised for their methodology, results, and conclusions. The findings of this review indicate that ML has been successfully applied to the detection of brain tumors in a variety of imaging modalities, including MRI and CT

Keywords: - ML, MRI, CT, CNN, ANN, SVM

1 Introduction

Brain tumor diagnosis using machine learning typically involves training a model on a dataset of medical images, such as MRI or CT scans, along with corresponding labels indicating the presence or absence of a tumor. The model can then be used to analyze new images and make predictions about whether a tumor is present. Additionally, machine learning techniques can be used to classify different types of brain tumors. Most body part abnormalities result in rapid tumor development, which is the leading cause of mortality globally. As per GLOBOCAN data, about 18.1 million new cases of cancer were diagnosed in 2018, resulting in 9.6 million annual deaths [1, 2].

Brain tumors are unregulated cell growths in the brain or the central nerve roots. These can be harmless (non-cancerous) or malignant (cancerous), it is important to note that the classification of tumors as non-cancerous or cancerous is a complex task that requires a combination of expert knowledge, clinical experience, and advanced technology. The use of machine learning in the process can help to improve the accuracy and efficiency of the diagnosis, but it should not replace the expertise of radiologists and pathologists and they can arise anywhere in the brain. Headaches, convulsions, nausea, and vomiting are frequent indications of brain tumors, as are visual or hearing loss, speech or memory issues, and emotional changes or behavior. Surgery, radiotherapy, chemotherapy, or a combination of these treatments may be used to treat brain tumors. Alternative therapies will be determined by the kind, location, and size of the tumor, as well as the patient's overall condition. Because diagnosis and treatment of brain tumors can improve healthcare, it is critical to seek medical assistance if you encounter any signs of a brain tumor [3].

The human brain is perhaps the most complicated part of the body, directing and integrating all bodily activities. It contains over 100 billion nerve cells (neurons) and billions of support cells (glia). Both chemical and electrical signals are used by neurons to interact with each other and send information all over the brain and the rest of the body. The brain is organized into various areas, each with its own set of specific tasks. The cerebrum is the brain's biggest structure and oversees conscientious cognition, memory, and judgment. The cerebellum is placed underneath the cerebrum and oversees motions and control [3, 4].

Brain tumor diagnosis using machine learning typically involves training a model on a dataset of medical images, such as MRI or CT scans, along with corresponding labels indicating the presence or absence of a tumor. The model can then be used to analyze new images and make predictions about whether a tumor is present. Additionally, machine learning techniques can be used to classify different types of brain tumors. A common approach is to use a convolutional neural network (CNN) for image classification. The model is trained on a dataset of brain scans, to learn to recognize the characteristic patterns associated with tumors. Once trained, the model can be applied to new scans to make predictions about whether a tumor is present. The strength of machine learning relies upon its capacity to create forecasting analytics from massive volumes of data with little or no existing understanding of the information or any hypotheses about the information. The artificial neural network (ANN), one of the most discussed current machine learning algorithms, is influenced by the biological neural networks that comprise animal species' brains. The processing element is the ANN's fundamental unit, which separates input data into distinct classes or categories [4].

The systematic finding of depictions required to produce insights using raw data is now possible with modern projection learning approaches [4]. Deep learning algorithms are one type of learning-based strategy that uses a hierarchical composition of input and output variables to turn raw input data into more complex data and aspects that allow for the detection of distinct properties [5]. Such techniques have been critical in recent engineering advances ranging from facial recognition and self-driving automobiles. Another approach is to use machine learning to analyze the results of other medical tests, such as blood tests, in combination with imaging results to improve diagnostic accuracy. It's important to note that machine learning models are not a replacement for clinical expertise and should be used to support and enhance the diagnostic process, not replace it [6-13].

Deep learning has evolved tremendously because of advancements in computing power and the open openness of the field of study. The utilization of CPUs and GPUs in deep learning projects has considerably expanded the size and complexity of strategy designs while decreasing the time necessary to train such methods from months to days. Because of the increased inquiry, faster testing has occurred, leading to more efficiency. Additionally, the introduction of open-source deep learning platforms such as TensorFlow, Kera's, PyTorch, Caffe, and others have increased access to technical achievements while also promoting idea interchange and execution across many domains [14, 15].

2 Literature Review

Vaishnavee and Amshakala [16] used SVM and self-organizing Map (SOM) algorithms to solve the problem of brain tumor classification. Histogram equalization was performed at the pre-processing step. The mean, severity, number of events, and variation were chosen to be four aspects to be classified. In the second step, they employed SOM clustering to locate the irregular brain groups and separate them. Furthermore, brain MR images were classified based on inter-clusters. In investigating the grey level co-existing texture matrix (GLCMs), it is calculated by first dividing the image into small overlapping regions, called windows, and then counting the number of occurrences of each grey level pair within each window. The resulting matrix can then be used to calculate a set of texture features such as contrast, correlation, energy, and homogeneity. Principal Component Analysis (PCA) is a technique used to reduce the dimensionality of a data set by identifying the directions (principal components) in which the data varies the most. It does this by transforming the original data into a new coordinate system, where the first axis (principal component) corresponds to the direction of maximum variance, the second axis corresponds to the direction of the second-highest variance, and so on. The resulting transformed data has reduced dimensionality, as the later principal component has less variance than the earlier one. PCA is used in various fields such as image compression, pattern recognition, and feature selection. The accuracy gained is recorded. Unfortunately, the authors did not examine the results of the design method, indicating that SVM and SOM were unnecessary.

Nie et al. [18] described a fully automated 3D-CNN feature extraction system that used T1, MRI, and DTI. The process typically involves training a 3D-CNN on a large dataset of labeled medical images, to learn to recognize the characteristic patterns associated with specific medical conditions, such as brain tumors. Once trained, the model can be applied to new images to extract a set of features that are relevant to the task at hand, such as the presence of a tumor and predicted results with 88.22% precision (specificity). The suggested approach, nevertheless, is difficult to solve and inappropriate for huge datasets.

Arikan et al. [26] developed a semi-autonomous interactive seed assessment SVM algorithm for the conflicts of brain tumors. The process typically involves training the SVM algorithm on a dataset of labeled seed images, to learn to recognize the characteristic patterns associated with specific seed traits, such as size, shape, color, and texture. Once trained, the model can be applied to new images to extract a set of features that are relevant to the task at hand, such as seed quality. A freely available BRATS 2015 dataset was utilized to assess performance. The BRATS-2015 dataset is a collection of MRI scans from patients with brain tumors, along with manual segmentations of the tumors by experts. The collection examines the outcomes of the novel technique. Their answer has a mean Dice Resemblance (DS) of about 81% to the core truth.

Ellwaa et al. [17] suggested a recursive random tree-based completely automated segmentation technique for MRI-based brain malignancies. One common approach is to use a 3D-CNN, which can process volumetric images and learn to recognize the characteristic patterns associated with brain tumors. The model can be trained on a dataset of labeled MRI scans, to learn to accurately segment the tumor regions in new images. The participant's accuracy about certain aspects of the data collection Iterative improvements was made to the algorithm utilized for random forest categorization. The method was put to the test during the BRATS-2016 dataset. Performance criteria for the individual with the most expertise result in beneficial consequences. Furthermore, no reason for the selection conditions was provided, and no accurate results were presented.

On the BRATS 2013 dataset, Abbasi and Tajeripour [21] suggested a 3D computerized interface for brain tumor identification and localization. ROIs (Region of Interest) is used for pre-processing; bias field correction and histogram transmission Bias field correction is a technique used to correct for non-uniformity in the intensity values of an image caused by factors such as scanner variability or patient movement. The goal is to equalize the intensity values across the image, making it easier for algorithms to accurately segment or classify the image. One of the most popular methods for normalization algorithms is segregated from the FLAIR picture environment. In this method for non-uniform intensity normalization in tumor detection is the use of adaptive histogram equalization (AHE), which can be applied to small regions of the image to enhance the contrast in regions that are affected by non-uniform intensity. This method can improve the visibility of tumors in images and make them more easily detectable by radiologists or computer-aided detection systems. HOG and LBP characteristics were input into a random forest classifier for learning tasks. They did, however, employ synthetic data for their trials and attained a 93% accuracy. Mehmood et al. [23] presented a useful approach for brain imaging and modeling utilizing magnetic resonance images. In the initial stages, there is an experiential, semi-automated 3D classification approach that uses SVM 95.53%, 99.49%, and 99.0% accuracy, sensitivity, precision, and 0.09 error to separate the brain and tumor areas from the MR sections. Investigations using self-generated datasets, on the other hand.

Das et al. [24] used texture-based characteristics to determine normal and diseased tissue samples. GMCH, Guwahati Hospitals provided 80 photos of aberrant and healthy tissue. Five classifier fusions analyzed the data from the photos and created a vector set of 172 attributes. Furthermore, six classifiers were employed to assess the efficiency of each set of features both in the cluster and independently. Using the entire dataset, the experimental findings indicated 100% accuracy and when comparing to separate feature sets, the feature set improved the average accuracy of classification to 98.6%. They determined computer-based might lead to improved diagnosis since childhood brain lesions are extremely dangerous. The recommended Grab cut technique [25] is used to segment genuine loss complaints, while the VGG-19 is used to create features that are subsequently integrated into series. While VGG-19 is trained on the ImageNet dataset, a large dataset of images with 1000 classes, and pre-trained weights are available for transfer learning. Transfer learning is the process of using a pre-trained model as a starting point to train a new model for a different task, such as medical image analysis. Entropy has built such technologies to detect consistently and easily.

Most of the approaches have been used while employing and constructing several smart as well as intelligent frameworks like machine learning approaches(Ali et al., 2021, 2022; Ali Raza et al., 2022; Asif et al., 2021; Aslam et al., 2021; Chayal and Patel, 2021; Dekhil et al., 2019; Fatima et al., 2020; Ghazal et al., 2022b; Khan et al., 2021; Muneer and Rasool, 2022; Saleem et al., 2022; T. Mohamed et al., n.d.), Fuzzy Inference systems (Abbas et al., 2019; Areej Fatima 1 and Adnan Khan 1, Sagheer Abbas 1, 2019; Asadullah et al., 2020; Aslam et al., n.d.; Gollapalli et al., 2022; Hussain et al., 2020; Ihnaini et al., 2021; T. A. Khan et al., 2020; Saleem et al., 2019), (Abbas, et al., 2019), (Al-Dmour, et al., 2022), Particle Swarm Optimization (PSO) (Iqbal et al., 2019; Kurdi et al., 2022), Fusion based approaches(Gai et al., 2020; Ma et al., 2020; Muneer and Raza, 2022; Sharma et al., 2021; Tabassum et al., 2021; Taher M. Ghazal, n.d.), (Saleem, et al., 2022) ,cloud computing (Bukhari et al., 2022; Dr. Adnan Khan and Sagheer Abbas, 2018; W. A. Khan et al., 2020; Khan, 2022; Naseer, 2022; Siddiqui et al., 2021; Ubaid et al., 2022), transfer learning(Abbas et al., 2020; Ghazal et al., 2022a)**,** Block chain technique(Abbas et al., 2021; Rehman et al., 2022), (Malik & Saleem, 2022) and MapReduce(Asif et al., 2021) which might be beneficial in developing evolving alternatives for the arising difficulties of creating smart cloud-based able to monitor management systems.

Table 1: Brain tumor detection methods

Reference	Methodology	Datasets	Results
Vaishnavee and Amshakala, [66]	PSVM	BRATS -2015	92 (Accuracy) 94 (Recall) 93 (Precision)
Ellwaa et al., [67]	Iterative Random Forest	BRATS-2016	
Nie et al., [68]	3D-CNN with SVM	Self Generated	89.9(Accuracy) 92.19(sensitivity) 88.22(Specificity) 84.44(PPR) 95.57(NPR)
Wasule and Sonar, [69]	SVM and K-NN	BRATS 2012	96 (Accuracy) 100 (Precision) 76 (Recall) 86.4 (F-Measure)
Fidon et al., [70]	CNN	BRATS-2013	
Abbasi and Tajeripour, [71]	RF	BRATS-2013	
Iqbal et al., [72]	CNN	BRATS 2015	82.29 (Accuracy)
Mehmood et al., [73]	Bow-Surf based SVM	LRH	99 (Accuracy) 0.96 (sensitivity) 0.99 (Specificity) 0.05 (FPR) 0.099 (FNR) 0.98 (F-Measure)
Das et al., [74]	Multiple classifiers fusion	GMCH	100 (Accuracy) 1.00 (AUC)
Saba et al., [75]	VGG-19	BRATS -2015 BRATS -2016 BRATS-2017	0.9878(Accuracy) 0.9963(Accuracy) 0.9967(Accuracy)

3 Conclusion

Brain tumor detection remains challenging due to tumor presence, mutable size, form, and arrangement. While tumor segmentation algorithms have demonstrated tremendous promise in analyzing and recognizing tumors in MRI images, much more effort is needed to properly segment and order the tumor section. Existing work has restrictions and difficulties in distinguishing tumor substructures and categorizing healthy and unhealthy photos. In summary, this research includes all key characteristics and current work, as well as its limits and challenges. It will help researchers learn how to perform new research in a timely and productive manner. Although deep learning techniques have made significant advances, a generic technique is still necessary.

Reference

1. Abbas, A., Abdelsamea, M.M., Gaber, M.M., 2020. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. Appl. Intell.
2. Abbas, S., Khan, M.A., Ata, A., Ahmad, G., Saeed, A., Anwar, N., 2019. Multi user detection using fuzzy logic empowered adaptive back propagation neural network. Neural Netw. World 29, 381–401.
3. Abbas, S., Talib, M.A., Ahmed, A., Khan, F., Ahmad, S., Kim, D.H., 2021. Blockchain-based authentication in internet of vehicles: A survey. Sensors 21.
4. Ali, N., Ahmed, A., Anum, L., Ghazal, T.M., Abbas, S., Khan, M.A., Alzoubi, H.M., Ahmad, M., 2021. Modelling supply chain information collaboration empowered with machine learning technique. Intell. Autom. Soft Comput. 30, 243–257.
5. Ali, N., Ghazal, T.M., Ahmed, A., Abbas, S., Khan, M. A., Alzoubi, H.M., Farooq, U., Ahmad, M., Khan, Muhammad Adnan, 2022. Fusion-based supply chain collaboration using machine learning techniques. Intell. Autom. Soft Comput. 31, 1671–1687.
6. Ali Raza, S., Abbas, S., M. Ghazal, T., Adnan Khan, M., Ahmad, M., Al Hamadi, H., 2022. Content Based Automated File Organization Using Machine Learning pproaches. Comput. Mater. Contin. 73, 1927–1942.
7. Areej Fatima 1, M., Adnan Khan 1, Sagheer Abbas 1, M.W. 1, 2019. Evaluation of Planet Factors of Smart City through Multi-layer Fuzzy Logic (MFL) 11, 51–58.
8. Asadullah, M., Khan, M.A., Abbas, S., Alyas, T., Saleem, M.A., Fatima, A., 2020. Blind channel and data estimation using fuzzy logic empowered cognitive and social information-based particle swarm optimization (PSO). Int. J. Comput. Intell. Syst. 13, 400–408.
9. Asif, M., Abbas, S., Khan, M. A., Fatima, A., Khan, Muhammad Adnan, Lee, S.W., 2021. MapReduce based intelligent model for intrusion detection using machine learning technique. J. King Saud Univ. - Comput. Inf. Sci.
10. Aslam, M.A., Zonain, M., Sattar, O., Saleem, M., n.d. Neurological Disorder Detection Using OCT Scan Image of Eye, in: 2022 International Conference on Cyber Resilience (ICCR),. pp. 1-13,.
11. Aslam, M.S., Ghazal, T.M., Fatima, A., Said, R.A., Abbas, S., Khan, M.A., Siddiqui, S.Y., Ahmad, M.,

2021. Energy-efficiency model for residential buildings using supervised machine learning algorithm. Intell. Autom. Soft Comput. 30, 881–888.
12. Bukhari, M.M., Ghazal, T.M., Abbas, S., Khan, M.A., Farooq, U., Wahbah, H., Ahmad, M., Adnan, K.M., 2022. An Intelligent Proposed Model for Task Offloading in Fog-Cloud Collaboration Using Logistics Regression. Comput. Intell. Neurosci. 2022.
13. Chayal, N.M., Patel, N.P., 2021. Review of Machine Learning and Data Mining Methods to Predict Different Cyberattacks, Lecture Notes on Data Engineering and Communications Technologies.
14. Dekhil, O., Naglah, A., Shaban, M., Ghazal, M., Taher, F., Elbaz, A., 2019. Deep Learning Based Method for Computer Aided Diagnosis of Diabetic Retinopathy, in: IST 2019 - IEEE International Conference on Imaging Systems and Techniques, Proceedings. Institute of Electrical and Electronics Engineers Inc.
15. Dr. Adnan Khan, Sagheer Abbas, 2018. Intelligent Transportation System for Smart-Cities using Fuzzy Logic. Lahore Garrison Univ. Res. J. Comput. Sci. Inf. Technol. 2, 64–79.
16. Fatima, S.A., Hussain, N., Balouch, A., Rustam, I., Saleem, M., Asif, M., 2020. IoT enabled Smart Monitoring of Coronavirus empowered with Fuzzy Inference System. Int. J. Adv. Res. Ideas Innov. Technol. 6, 188–194.
17. Gai, K., Guo, J., Zhu, L., Yu, S., 2020. Blockchain Meets Cloud Computing: A Survey. IEEE Commun. Surv. Tutorials 22, 2009–2030.
18. Ghazal, T.M., Abbas, S., Munir, S., Khan, M. A., Ahmad, M., Issa, G.F., Zahra, S.B., Khan, Muhammad Adnan, Hasan, M.K., 2022a. Alzheimer disease detection empowered with transfer learning. Comput. Mater. Contin. 70, 5005–5019.
19. Ghazal, T.M., Noreen, S., Said, R.A., Khan, M.A., Siddiqui, S.Y., Abbas, S., Aftab, S., Ahmad, M., 2022b. Energy demand forecasting using fused machine learning approaches. Intell. Autom. Soft Comput. 31, 539–553.
20. Gollapalli, M., Atta-Ur-Rahman, Musleh, D., Ibrahim, N., Khan, Muhammad Adnan, Abbas, S., Atta, A., Khan, Muhammad Aftab, Farooqui, M., Iqbal, T., Ahmed, M.S., Ahmed, M.I.B., Almoqbil, D., Nabeel, M., Omer, A., 2022. A Neuro-Fuzzy Approach to Road Traffic Congestion Prediction. Comput. Mater. Contin. 73, 295–310.
21. Hussain, A., Anwar Hussnain, S., Fatima, A., Siddiqui, S.Y., Saeed, A., Af Saeed, Y., Ahmed, A., Khan, M.A., 2020. A Novel Approach for Thyroid Disease Identification Empowered with Fuzzy Logic. IJCSNS Int. J. Comput. Sci. Netw. Secur. 20.
22. Ihnaini, B., Khan, M. A., Khan, T.A., Abbas, S., Daoud, M.S., Ahmad, M., Khan, Muhammad Adnan, 2021. A Smart Healthcare Recommendation System for Multidisciplinary Diabetes Patients with Data Fusion Based on Deep Ensemble Learning. Comput. Intell. Neurosci. 2021.
23. Iqbal, K., Khan, M.A., Abbas, S., Hasan, Z., 2019. Time complexity analysis of GA-based variants uplink MC-CDMA system. SN Appl. Sci. 1, 1–8.
24. Khan, M.F., Ghazal, T.M., Said, R.A., Fatima, A., Abbas, S., Khan, M. A., Issa, G.F., Ahmad, M., Khan, Muhammad Adnan, 2021. An iomt-enabled smart healthcare model to monitor elderly people using machine learning technique. Comput. Intell. Neurosci. 2021.
25. Khan, T.A., Abbas, S., Ditta, A., Khan, M.A., Alquhayz, H., Fatima, A., Khan, M.F., 2020. IoMT-based smart monitoring hierarchical fuzzy inference system for diagnosis of covid-19. Comput. Mater. Contin. 65, 2591–2605.
26. Khan, W.A., Abbas, S., Khan, M.A., Qazi, W.M., Khan, M.S., 2020. Intelligent task planner for cloud robotics using level of attention empowered with fuzzy system. SN Appl. Sci. 2, 1–13.
27. Khan, Z., 2022. Used Car Price Evaluation using three Different Variants of Linear Regression 1, 40–
28. Kurdi, B. Al, Raza, H., Ibrahim, A., Aslam, M.A., Zonain, M., Sattar, O., Saleem, M., 2022. Estate Price Predictor for Multan City Townships Using Machine Learning, in: 022 International Conference on Cyber Resilience (ICCR), Dubai, United Arab Emirates, 2022,. UAE, pp. 1–5.
29. Ma, F., Sun, T., Liu, L., Jing, H., 2020. Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. Futur. Gener. Comput. Syst. 111, 17–26.
30. Muneer, S., Rasool, M.A., 2022. A systematic review : Explainable Artificial Intelligence (XAI) based disease prediction 1, 1–6.
31. Muneer, S., Raza, H., 2022. An IoMT enabled smart healthcare model to monitor elderly people using Explainable Artificial Intelligence (EAI) 1, 16–22.
32. Naseer, I., 2022. Removal of the Noise And Blurriness using Global & Local Image Enhancement Equalization Techniques 1.
33. Rehman, A., Abbas, S., Khan, M.A., Ghazal, T.M., Muhammad, K., Mosavi, A., 2022. A secure healthcare 5 . 0 system based on blockchain technology entangled with federated learning technique. Comput. Biol. Med. 150, 106019.
34. Saleem, M., Abbas, S., Ghazal, T.M., Adnan Khan, M., Sahawneh, N., Ahmad, M., 2022. Smart cities:

Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. Egypt. Informatics J.

35. Saleem, M., Khan, M.A., Abbas, S., Asif, M., Hassan, M., Malik, J.A., 2019. Intelligent FSO Link for Communication in Natural Disasters empowered with Fuzzy Inference System. 1st Int. Conf. Electr. Commun. Comput. Eng. ICECCE 2019 1–6.
36. Sharma, P., Jindal, R., Borah, M.D., 2021. Blockchain Technology for Cloud Storage. ACM Comput. Surv. 53, 1–32.
37. Siddiqui, S.Y., Haider, A., Ghazal, T.M., Khan, M.A., Naseer, I., Abbas, S., Rahman, M., Khan, J.A., Ahmad, M., Hasan, M.K., Mohammed, A., Ateeq, K., 2021. IoMT Cloud-Based Intelligent Prediction of Breast Cancer Stages Empowered with Deep Learning. IEEE Access 9, 146478–146491.
38. T. Mohamed et al., n.d. Intelligent Hand Gesture Recognition System Empowered With CNN, in: 2022 International Conference on Cyber Resilience (ICCR), Dubai,. pp. 1–8.
39. Tabassum, N., Ditta, A., Alyas, T., Abbas, S., Alquhayz, H., Mian, N.A., Khan, M.A., 2021. Prediction of Cloud Ranking in a Hyperconverged Cloud Ecosystem Using Machine Learning. Comput. Mater. Contin. 67, 3129–3141.
40. Taher M. Ghazal, et al., n.d. A review on security threats, vulnerabilities, and counter measures of 5G enabled Internet-of-Medical-Things. Inst. Eng. Technol. 16, 421–432.
41. Ubaid, M., Arfa, U., Muhammad, H., Muhammad, A., Farooq, S., Saleem, M., 2022. Intelligent Intrusion Detection System for Apache Web Server Empowered with Machine Learning Approaches 1.
42. Abbas, S., Fatima, A., Asif, M., Saleem, M.: Energy optimization in smarts homes by using fuzzy inference system, January 2019
43. Aslam, M.A., Zonain, M., Muneer, S., Sattar, O., Salahat, M. and Saleem, M., 2022, October. Neurological Disorder Detection Using OCT Scan Image of Eye. In 2022 International Conference on Cyber Resilience (ICCR) (pp. 01-13). IEEE.
44. Al-Dmour, N.A., Salahat, M., Nair, H.K., Kanwal, N., Saleem, M. and Aziz, N., 2022, October. Intelligence Skin Cancer Detection using IoT with a Fuzzy Expert System. In 2022 International Conference on Cyber Resilience (ICCR) (pp. 1-6). IEEE.
45. Saleem, M., Khadim, A., Fatima, M., Khan, M.A., Nair, H.K. and Asif, M., 2022, October. ASSMA-SLM: Autonomous System for Smart Motor-Vehicles integrating Artificial and Soft Learning Mechanisms. In 2022 International Conference on Cyber Resilience (ICCR) (pp. 1-6). IEEE.
46. Malik, R., Raza, H. and Saleem, M., 2022. Towards A Blockchain Enabled Integrated Library Management System Using Hyperledger Fabric: Using Hyperledger Fabric. International Journal of Computational and Innovative Sciences, 1(3).