

Machine Learning and Deep Learning Algorithms for Cancer Diagnostic Optimization

Mohammed Nasser Hussain¹, Abhigna Reddy Pothula², Kotha Nikhil Reddy³, Talla Vivek Sagar⁴

^{1,2,3} Students, Department of Computer Science and Engineering, Kakatiya Institute Of Technology and Science, Hanamkonda, Telangana, India.

⁴ Student, Department of Electronics and Communication Engineering, Kakatiya Institute Of Technology and Science, Hanamkonda, Telangana, India.

Abstract - Recently, advances in machine learning and artificial intelligence have made these techniques increasingly prominent. Companies and institutions have begun investing in healthcare research to improve the accuracy of disease prediction because of its widespread popularity and effective pattern detection and categorization capabilities. However, there are numerous difficulties that arise while employing these methods. The lack of a huge data set for medical pictures is one of the biggest challenges. This study aims to provide a reasonable introduction to deep learning in medical image processing, beginning with theoretical foundations and progressing to practical implementations. Deep learning (DL) has become increasingly popular due to a number of computer science discoveries, according to a new study. To get a better grasp of neural networks, the next step was to familiarise ourselves with the principles. That's why convolutional neural networks (CNNs) and deep learning are used. This gives us a better idea of why deep learning is advancing so quickly in so many different application domains, including medical image processing.

Key Words: Machine Learning, Deep Learning, CNN, Cancer, Algorithm, ANN.

1. INTRODUCTION

When it comes to technical advancements, scientific research has always played an important role. Medicinal research has accelerated in recent years, and AI has made significant strides. Medical research is taking use of AI's sophisticated methods such as machine learning (ML), artificial neural networks (ANN), and deep learning. Biomedical scientists are expected to begin using it within a matter of months or years. That's mostly because there's no need that the answer have a linear shape. Since no specialised method is required to identify the condition, Deep Neural Networks (DNN) are perfect for disease recognition utilising scans. Because it learns by example, data is more crucial than algorithms in identifying the condition. Many health institutions are working with limited financial resources to upgrade their old infrastructure and legacy technology, according to a recent survey. An effort is being made by the medical sector to use machine learning technologies such as artificial neural networks and deep neural networks in order to reduce costs, improve assessment accuracy, and make wise decisions in healthcare management in order to move towards value-based care. AI and ANN algorithms are being used in the treatment of illnesses including cancer and heart disease, according to a

new health care research. Medical applications of artificial neural networks (ANNs) include cancer classification, voice recognition, picture analysis/interpretation, and so on. There have been three major fields of machine learning since the introduction of computers in the 1950s and 1960s: statistical approaches, symbolic learning, and neural networks. Using machine learning techniques, researchers have shown that the systems can resolve issues by learning from the data they get through their observations. Producing mathematical models that can be trained on input data and then used to generate valuable outputs is the correct objective to strive towards. An optimization algorithm is used to fine-tune machine learning approaches so that they give reliable data training predictions. Using these lessons as a starting point, models may then be used to make accurate predictions based on fresh, unobserved data. Training and validation data sets that are separate from one another are often utilised in generalisation models to provide feedback for further model tweaking. Once the final model has been trained and tuned, it is tested on a test set to see how it performs when faced with new and unexpected data. Machine learning may be broadly divided into numerous types based on how the models utilise input data in actual usage. Reinforcement learning involves creating agents that, while maximising an objective function, learn from their environment by making mistakes and then trying again. Reinforcement learning is a common method of teaching computers to learn. Deep Mind's machine learning systems may be seen in go-playing, which is an example[1]. Computers are given free rein to sift through massive amounts of data in search of patterns on their own, known as unsupervised learning. An example of unsupervised learning known as clustering is one of the most often used techniques. Supervised learning comprises the majority of today's machine learning systems. Using a collection of previously labelled or assembled data, the computer generates new, previously unseen data sets with the right labels based on these previously labelled data sets. All of the input/output examples are used to teach the model, which is used for specific data-handling functions. Some examples of the many medical imaging-related issues that may be addressed using supervised learning include malignant skin lesions, cardiac risk factors from retinal fundus pictures, and brain tumour identification from MRI images[2]. The basic and most significant job of machine learning is to make data learn automatically to describe complex patterns and make smart decisions based on the knowledge. There are several subfields within the area of machine learning, which has a long history. It's receiving a lot of attention is deep learning. Image and video object detection, segmentation, classification, and recognition are all shown in Figure.1, which shows the

relationship between the approaches now regarded state-of-the-art and considered effective.

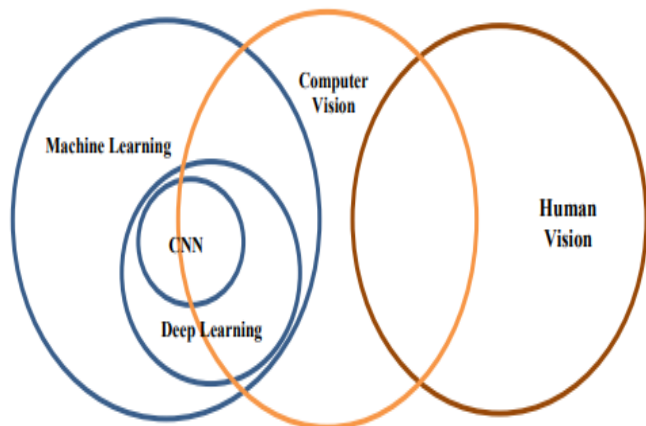


Fig -1: The relation between machine learning, deep learning, CNN, human vision and computer vision

Figure 1 shows the relationship between computer vision, human vision, deep learning, and CNN. Pattern recognition is the subject of much study, and as technology advances, so can the complexity of medical diagnosing jobs. When it comes to analysing vast amounts of data using machine learning algorithms, there hasn't been a major breakthrough until recently. As computer speed and memory have improved over time, machine learning algorithms have been able to create and learn from a wide variety of training data[3]. With ever-growing amounts of data, deep learning has developed as an effective method for analysing and synthesising the information. Since artificial neural networks can learn any function with just one hidden layer, they are considered universal function approximators. When processing power and memory are adequate, it is possible to build deep neural networks, which consist of multiple layers of neural networks. Artificial neuron layers are used to simulate the structure of a DNN. Deep learning has three key advantages. Simplicity: With deep networks, you get large architectural components, network layers, that are repeated several times to construct massive networks. Scalability: There is no limit to the size of datasets that can be processed by deep learning models. When dealing with enormous datasets, other competing approaches such as kernel machines run into serious computing issues. Domain transfer: The features gained by a model trained in a task are a series of connected tasks that may include limited information. Among the many applications of deep neural networks, such as image identification and classification, CNNs have shown to be particularly effective.

A typical machine learning model is taught to perform meaningful actions based on manually built features extracted from raw data or from other basic machine learning models. As a result of deep learning, computers can learn from large datasets without the need for any human intervention. By far, the most common model in deep learning is an ANN in one form or another. Deep learning approaches are popular because of their concentration on learning features, i.e. automatically learning information representations[4].

There were an estimated 18.1 million new cancer cases and 9.6 million deaths worldwide in 2018, according to a World Health Organization (WHO) report released in 2018 [7]. Increasing rates of cancer-related deaths could pose a threat to public health. In the foreseeable future, a frightening

situation. Abnormalities can be prevented if they are discovered early enough.

the frequency of deaths. There are a plethora of time-consuming, expensive, and painful cancer diagnostic procedures and Detection and treatment can be delayed by these processes. As a rule, the patient in the event of a misdiagnosis, has a pointless biopsy performed. The new technique, i.e. Machine learning and artificial neural networks are being employed in this field, resulting in early results. Many types of cancer can be detected. The radiologist has benefited greatly from the use of automated analysis. aiding in diagnosis and reducing errors by serving as a second set of eyes, how many mistakes there are. Despite this, there are only a few viable options. Thus, This study will make new use of open source technologies that have recently emerged. a feasible and efficient plan of attack Precision and false negativity will be reduced as a result of this change. Rule-based categorization models for predicting liver illness differ significantly from those without rules, according to Kumar and Sahoo [3]. The most accurate classification model is based on a rule-based classification model with a Decision Tree technique. In comparison to Rule Induction, SVM, ANN, and Naive Bayes, the predicted model with DT technique achieves the highest accuracy, sensitivity, specificity, and Kappa values of 98%, 95.8%, and 0.983% while the SVM model performs poorly with an accuracy of only 82.33 percent, 68.03 percent, and 0.801%. The best performance of the model without rules -RI, Accuracy 82.68 percent, Sensitivity 86.34 percent, Specificity 90.51 percent and Kappa 0.619, is almost identical to the worst performance of the rule-based classification model of SVM- Accuracy 82.33 percent, Sensitivity 68.03 percent, Specificity 91.28 percent and Kappa 0.801 and the accuracy of the chi-square test is 76.67 percent. This is a critical distinction between medical imaging's deep learning approaches. Convolutional neural networks are often the source of the intrigue around deep learning. An exciting new discovery of our day, 3D printing is a useful tool for quickly creating and displaying 3D pictures and other 3D representations of data[5]. Before CNNs could be used effectively, these properties had to be developed manually or sculpted by less sophisticated machine learning models. If and when a feature or function could actually be used, it gained knowledge from that information. Many of the handmade picture features are often discarded since they are less helpful than CNN feature detectors [6].

2. LITERATURE SURVEY

New technologies in the area of artificial intelligence have developed and shaped our business during the last several years. In 2006, a new era in machine learning, dubbed deep structured learning or hierarchical learning or more often referred to as deep learning, developed. [7, 8] Companies like Microsoft, Google, IBM Research, Baidu, and Facebook are also investing in this research and development by building new open-source software and libraries, as are researchers from the University of Toronto, New York University, the University of Montreal, and Stanford University. UC-Berkley, UC-Irvine, University College London, University of Michigan, and the Massachusetts Institute of Technology all saw an uptick in their deep learning research[7]. Some of the world's most well-known healthcare institutions and

organisations have also come together to strive toward the best possible solution for massive medical imaging. It is a simple and uncomplicated idea that has provided CNN a tremendous jump in performance. Using an ensemble of models rather than a single model tends to yield better results. Stochastic sampling of the neural network is used to generate a random sample called a dropout. Consistently deleting neurons during training results in employing inconsistently diverse networks for each batch of data and altering the weights of the trained network based on the optimization of distinct network developments. These businesses are putting a lot of money on imaging-based medical diagnostics. Artificial neural networks, or "new-generation neural networks," were the first to introduce the notion of deep learning. A typical example of a model with a deep architecture is feedforward neural networks (FFNN) with many hidden layers, which are often referred to as DNN. Historically, a well-known approach for figuring out these networks' parameters is back-propagation, which became famous in the 1980s. For learning networks with more than a few hidden layers, BP alone did not perform effectively in practise[8]. For the purpose of examining the characteristics reproduced by deep convolutional networks from image data, Zeiler and Fergus introduced an innovative and comprehensive visualisation method that established a top-down generative method in the reverse direction of the classification network and provided insight into the functioning of intermediate feature layers. To highlight the power of deep networks, we may look at their ability to produce acceptable features and to discriminate together.



Fig -3: Gartner Hyper cycle graph to analyze the history of artificial neural network technology.

It's a snapshot of how a certain technology or application has changed through time. An understanding of the five stages of technology's life cycle — its inception, apogee of inflated expectations, trough of disappointment, incline of illumination, and plateau of output — may help with distribution planning and control. "Hype cycle" was used by Le Deng in his study to describe Figure.3 and its several generations of neural networks[9]. The "second generation" of neural networks was at its peak in the late 1980s and early 1990s, when core activities ("expectations" or "media hype" on the vertical axis) were at their height. It is at this time period, while the DBN is being used to initialise the DNN, that a rapid training technique known as the Deep Belief Network was invented in 2006. It's a snapshot of how a certain technology or application has changed through time. Five phases: technological trigger, peak of inflated expectations, valley of disappointment, and plateau of production give information into how to distribute the product in the most efficient manner. Since the 1990s, computer vision and image recognition have relied on deep models using convolutional frameworks like CNNs. Also, these are some of the earliest deep models that have shown to be successful, long before arbitrarily deep models were thought to be possible. It is the neocogitron that Fukushima proposed in 1980, which is acknowledged as the model on the computer side that drives CNN. The extracted characteristics are organised in a neural network with two unique layers: the S-layer as an extractor and the C-layer as structured connections. Many applications, including as handwriting recognition and other pattern identification challenges, have made use of the multi-layered, hierarchical ANN. The convolution operation, which is also known as a kernel, may be used to perform various operations on pictures by selecting different kernels[10]. A convolution operator based on the use of random matrices might provide some intriguing results in terms of edge detection, blurring, sharpening, etc. This also led to the MNIST database being the standard benchmark for



Fig -2: Gartner Hyper cycle graph representing the evolution of technology

There's an easier, better way to look at how ANN has evolved through time: utilise a "hype cycle," which shows how certain strategies have matured, adopted, and been implemented in society as a whole over time. Figure 2 shows a new version of Gartner's Hyper cycles graph for 2012.

digital recognition after LeNet's debut. The first CNN based on neocognitron is LeNet, developed by Le Cun et al. It consists of two pairs of convolutional and subsampling layers, as well as a fully connected layer and an RBF layer for classification. However, although Krizhevsky et al.'s invention of AlexNet kick-started the period of CNN implementation, it was LeNet that first introduced the ImageNet classification framework to the world. Simulating AlexNet on two GPUs helps reduce the amount of time it takes to train the neural network. In addition, augmentation, a method for adding data that aids in picture translation, horizontal reflection, and patch extraction, is used in this process. In 2012, the most important advancement in the area of image processing was made public[11]. You have to use 1.2 million high-resolution photos in order to train an ImageNet LSVRC model and sort them into one of 1,000 distinct categories. Error rates in the test set of 150k photos were significantly reduced by the adoption of a deep CNN technique. Simonyan and Zisserman looked at a variety of designs and came up with the VGG model, which they considered to be a simple yet effective solution. With 19 layers, the VGG is deeper than previous models, but the design of the VGG is far more streamlined. Layers of three-by-three convolutions are followed by two-by-two convolutional pools. Networks that are formed using ResNet are 10 times deeper than those that are produced with other networks [4]. In contrast, Veit et al. believe that ResNet serves as an aggregation of shallow networks, which is an interesting take. The expressway enables ResNet to function as an independent network collection, making each network shallower than the unified ResNet. This also explains why the ultra-deep architecture is able to accomplish gradient without it disappearing.

3. LIVER DIAGNOSTIC TESTS

The best technique to identify liver disease is to do invasive and non-invasive testing on a person with a comprehensive medical history. Liver function tests are the most essential and major kind of liver diagnostic test used to monitor changes in liver metabolism (LFTs). Infiltrating liver disorders, cholestasis, hepatocellular damage, and impaired hepatic synthesis are all reflected in these diverse biochemical alterations. The liver and biliary system status is taken into consideration by the LFTs, which are carried out using a simple blood test. However, the liver's total function cannot be evaluated by a single test. As a group, the data may be used to estimate the likelihood of liver disease, its possible causes, and its severity[12]. Additionally, liver function laboratory tests may also be performed to evaluate the course of the illness and the outcomes of therapy. As a matter of fact, the name "liver function tests" is a misnomer since most tests don't really examine all aspects of the liver's operation. Damage to liver cells, such as aminotransferases and alkaline phosphatases, and bile duct blockage may be detected by measuring the enzyme concentrations at a variety of various levels. The liver produces enzymes that aid in the absorption of fat. These tests may be split into three categories: liver function, biliary blockage, and cell damage. There is a large body of medical research on LFTs that should be evaluated in light of the patient's clinical opinion in order to illustrate how they are examined and interpreted. Patients should be assessed using their symptoms and physical examinations, risk factors for hepatitis, and their family history of hereditary liver

disease as well as their alcohol or illicit drug use as well as their gender, their age, their age of onset, and their mental state. It is crucial to do tests such as X-rays or liver imaging scans in order to diagnose illness. Patients' treatment, government health care services, and financial implications are all dependent on physicians' ability to properly interpret results from these tests. There are many different functions performed by the liver, making it one of the most difficult organs to understand. As soon as it starts to be impacted, the body suffers harm. It takes a long time for the body to see the results. It is one of the most self-regenerating organs. The liver's ability to regenerate and heal itself is well-known. When damage is discovered, it can no longer be repaired. Alcohol intake is a leading cause of chronic liver disease, which is why it is also known as Alcoholic liver disease (ALD). It is the third most frequent reason for liver transplants and is most common in Western countries. Studies have shown that even at very modest levels of alcohol use — as little as 30 grammes per day — the risk of getting ALD increases with increasing ethanol concentration in various drinks. As low as 20 grammes of alcohol per day is considered the safest daily alcohol consumption limit, according to several studies. Males who drink more than 80 grammes of alcohol per day for 10 years are at the greatest risk of having ALD, whereas women are 2–4 times more likely to acquire ALD than men. One of the leading causes of acute liver injury and liver failure is the use of alcohol. The consequences of excessive alcohol drinking are frightening and may lead to ALD.

4. FEEDFORWARD BACKPROPAGATION NEURAL NETWORK ALGORITHM

There are many different types of neural networks. A neural network is a predictive model with the capacity to learn, evaluate, and organise data, and then anticipate test outcomes. Pattern categorization functions and other modelling tools have been approximated using several types of neural network models. Multilayer feedforward networks seem to be the most often used. Nonlinear mapping difficulties may be effectively modelled using feedforward neural networks. Standard backpropagation training algorithms, which use gradient descent optimization procedures in the weight space of a network with a given topology, are often used to train these neural networks. Only when the network design is selected right can this form of training be considered helpful. Feedforward neural networks are the most common kind of neural network used in medical diagnostics. These networks are honed using a predetermined collection of patterns called a training set. A similar hypothesis was made in this investigation. The Levenberg Marquardt method is used to train a multilayer perceptron feedforward backpropagation neural network for classification. Local minima are avoided and a more accurate cost function is produced by using the LM method for training. There are three layers in the system: an input layer that processes data in a forward manner, a hidden layer that processes data in a reverse direction, and an output layer that processes data in a reverse way. Using a feedforward neural network is a nonparametric estimate of statistical models for extracting nonlinear relationships from the input data. Two stages are included in the algorithm's training process.

5. PERFORMANCE MEASURE

A classifier's total performance may be judged by its performance accuracy. There are two independent metrics of a classifier's performance: sensitivity and specificity. Research in medicine looks at the proportion of properly recognised benign tumours using sensitivity, whereas the percentage of correctly categorised malignant tumours is measured using specificity.

6. RESULTS AND DISCUSSION

There must be a comparison of neural networks trained with various parameters in order to find the best one. This must be done through examining the neural network's performance. Table.1 shows the outcomes of the train(lm) and table.1 experiments. 2. displays the Train (rp). Data from a test is used to construct a performance metric that can be relied upon to be accurate. The training method will not make use of this particular collection. Sensitivity, specificity, and accuracy are three metrics used to measure the effectiveness of a neural network.

Table.1. Results obtained on BUPA liver disorder data set using (trainlm)

Sl No	train(lm)	NNeurons	Sensitivity %	Specificity %	Accuracy %
1	FF	20	84	85	86
2	CC	20	86	80	87
3	FF	30	86.5	81	87
4	CC	30	90	82	88
5	FF	40	91	82	88
6	CC	40	91.5	83	89
7	FF	50	94	84	89
8	CC	50	94	84	89.5

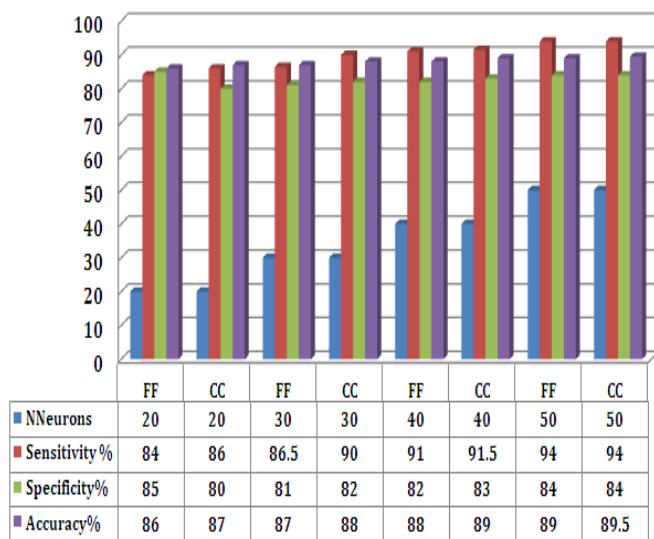


Fig -4: Comparison of classifiers using the train(lm) algorithm.

Table.2. Results obtained on BUPA liver disorder data set using (trainrp)

Sl No	train(lm)	NNeurons	Sensitivity %	Specificity %	Accuracy %
1	FF	20	85	70	76
2	CC	20	87	72	78
3	FF	30	89	73	79
4	CC	30	89.5	74	80
5	FF	40	91	77	83
6	CC	40	92	74	84
7	FF	50	89	73	83
8	CC	50	89.8	735	83.5

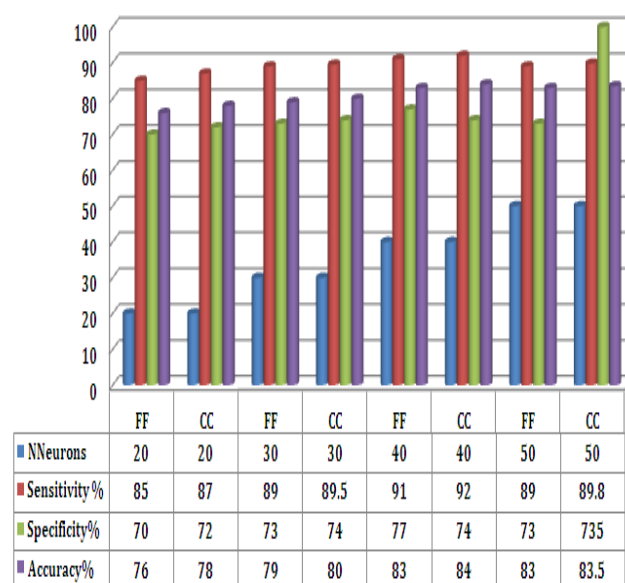


Fig -5: Comparison of classifiers using train(rp) algorithm

7. CONCLUSION

Based on MATLAB's trainlm and trainrp, the suggested model compares chosen classification methods on ANN to identify liver condition. The comparison is shown in a visual manner. Using the trainlm technique, the CCN approach outperforms the feed forward back propagation algorithm, as shown in Fig. 5. It shows the improved sensitivity, specificity, and accuracy of the cascade correlation algorithm when the training procedure is altered. A final conclusion is that the cascade correlation method employing both training techniques is more effective. Liver cancer will be diagnosed more often as a result of this research.

ACKNOWLEDGEMENT

We Thank to HoD, Principal, Faculties and Management of Kakatiya Institute Of Technology and Science, Hanamkonda, Telangana, India .

REFERENCES

1. N. Shahid, T. Rappon and W. Berta, "Applications of artificial neural networks in health care organizational decision-making: A scoping review", PLOS ONE, vol. 14, no. 2, 2019.
2. S. Srinivas, R. Sarvadevabhatla and N. Prabhu, "An introduction to deep convolutional neural nets for computer vision", deep medical image analysis, pp. 25- 52, 2017.
3. G. Hinton, S. Osindero, and Y. Teh. A fast learning algorithm for deep belief nets Neural Computation, 18:1527–1554, 2006.
4. D. Ciresan, U. Meier, and J. Schmidhuber. Multi-column deep neural networks for image classification. In Proceedings of Computer Vision and Pattern Recognition (CVPR). 2012.
5. K. Jarrett, K. Kavukcuoglu, and Y. LeCun, "What is the best multistage architecture for object recognition?", in Proceedings of International Conference on Computer Vision, pages 2146–2153. 2009.
6. K. Kavukcuoglu, P. Sermanet, Y. Boureau, K. Gregor, M. Mathieu, and Y. LeCun. "Learning convolutional feature hierarchies for visual recognition.", in Proceedings of Neural Information Processing Systems (NIPS), 2010.
7. K. Fukushima, "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position", Biological Cybernetics, vol. 36, no. 4, pp. 193-202, 1980. Available: 10.1007/bf00344251.
8. Krizhevsky, I. Sutskever and G. Hinton, "ImageNet classification with deep convolutional neural networks", Communications of the ACM, vol. 60, no. 6, pp. 84- 90, 2017.
9. Veit, M. Wilber and S. Belongie, "Residual networks are exponential ensembles of relatively shallow networks", arXiv, 2016.
10. Venkata Ramana, M. Babu and N. Venkateswarlu, "A critical study of selected classification algorithms for liver disease diagnosis", International Journal of Database Management Systems, vol. 3, no. 2, pp. 101-114, 2011.
11. V. Kamalallannan and M. Ramyachitra, "An experimental analysis of different classification techniques for diabetic dataset", International Journal of Advanced Research in Computer Science and Software Engineering, vol. 6, no. 2, p. 14, 2016.
12. H. Dong, G. Yang, F. Liu, Y. Mo and Y. Guo, "Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks", Communications in Computer and Information Science Medical Image Understanding and Analysis, pp. 506-517, 2017.