JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review on detection of Brain Tumor and Myocardial Infarction and prediction of Lung Cancer and Diabetes Mellitus with Machine Learning

[1]Nikhil Giramkar, [2]Shubham Rane, [3]Abhishek More, [4]Rupesh Bodkhe, [5]Shraddha Khonde
[(1,2,3,4)] Student, [5]Assistant Professor
[(1,2,3,4,5)] Department of Computer Engineering,
Modern Education Society's College of Engineering,
19, Late Prin. V.K. Joag Path, Wadia College Campus, Pune – 411001.

Abstract: Advancements in the application of Machine Learning and recent developments in its algorithms has opened a path for great progress in medical sciences. Due to this data driven approach in prediction of diseases, we can cure several chronic disorders at an early stage of life. The literature aims at enlightening the contemporary evolution in detection of brain tumour, myocardial infarction and prediction of lung cancer and diabetes mellitus performed by the research scholars worldwide using various machine learning algorithms. We also aim at conducting a comparative study and deriving important conclusions on the survey.

Keywords: Machine Learning, Diabetes Mellitus, Lung Cancer, Myocardial infarction, Brain Tumour.

I. INTRODUCTION

Machine Learning (ML) is a branch of computer science which has various interdisciplinary applications and has proved to be very efficient in the medical diagnosis. Several data mining techniques like extraction, pre-processing of data, model planning, model building and generation of results give worthwhile insights to researchers. Machine learning algorithms are an important part of this process as they apply optimization, probabilistic and statistical techniques to learn from data generated from past experience and deploy it in decision making. The study aims at surveying four major deadly diseases, lung cancer, brain tumour, diabetes mellitus and myocardial infarction.

The growth of cancerous cells in lungs is called lung cancer. The mortality rate of both men and women has expanded due to the increasing rate of incidence of cancer. Lung cancer is a disease where cells in the lungs multiply uncontrollably. If the prediction of lung cancer is done at an early stage, many lives can be saved and accurate prediction can help the doctors to begin their treatment. A Computed Tomography (CT) scan is used to find the position of tumour and identify the level of cancer in the body. Medical image segmentation and classification play an important role in medical research field. The patient CT lung images are classified into normal and abnormal category via machine learning algorithms.

Diabetes Mellitus (DM), commonly known as diabetes is one of the deadliest diseases in the world. The World Health Organization (WHO) ranked Diabetes Mellitus at 9th position for the "Top 10 Leading causes of Death Globally" in the year 2020 which was ranked 12th in the year 2000 [1]. Insulin is responsible for regulating the blood sugar level in the body. Diabetes occurs either due to insufficient production of insulin by the beta-cells of pancreas [2], or unresponsiveness of body to the insulin produced [3], various environmental and genetic factors also play an important role in this [4]. Diabetes Mellitus may lead to many complications if left untreated. Some of them include cognitive impairment, cardiovascular disease, diabetes ketoacidosis, stroke, nerve damage, foot ulcers, hyperosmolar hyperglycaemic state, or even death [5]. Machine learning algorithms help in predicting whether a person is suffering from Diabetes Mellitus or not.

Cardiovascular diseases (CVD) are the number one cause of death globally. According to a WHO report, an estimated 17.9 million people died from CVDs in 2016, representing 31% of all global deaths. Of these deaths, 85% are due to heart attack and stroke [6]. Heart attack also known as Myocardial Infarction (MI), occurs when blood flow decreases or stops to a part of the heart, causing damage to the heart muscles. ECG signals are used for detection of myocardial infarction and feed to various Machine Learning algorithms to detect it with high accuracy.

Brain tumour is a collection of abnormal cells in your brain. The condition is hard to cure because the brain has a complicated structure and the tissues are interconnected with each other in a complex manner. Despite many existing approaches, robust and efficient segmentation of brain tumour is still an important and challenging task. Brain abnormalities like injuries, damage, tumour-related causes, affects and symptoms, have been analysed for tumour recognition by using data mining, image processing and machine learning techniques. Abnormalities are analysed using Magnetic Resonance Imaging (MRI), image cryptography, electroencephalogram (EEG) and computed tomography (CT) related data. MRI is most often used for the detection of tumours, lesions, and other abnormalities in soft tissues, such as the brain. Before any treatment, the tumour has to be identified in MR images. With the advancements in machine learning, early detection of brain tumour with a great accuracy is now possible.

II. REVIEW OF LITERATURES

A literature survey for recent advancements in prediction of lung cancer, diabetes mellitus and detection of brain tumour and myocardial infarction and a comparative study of a few papers has also been provided as follows:

2.1 Lung Cancer

Many works have already been proposed in prediction of lung cancer. Among them, A. Bankar *et. al.* [7] performed symptom-based analysis among people of different age groups to predict lung cancer. They took the dataset from a website which has “Lung Cancer Dataset”. They applied different algorithms and found that XGBoost, Random Forest and Decision Tree outperformed others with 100% accuracy.

J. Alam *et al.* [8] proposed “multi-stage lung cancer detection and prediction using multi-class SVM classifier”, describing an effective algorithm using Support Vector Machine (SVM) for lung cancer detection, diagnosis and its capability to anticipate the possibility of lung cancer. A proper algorithm was developed using MATLAB and it had image processing techniques which helped in image enhancement, detection and segmentation. Their proposed algorithm gave 97% accuracy in detection and 87% accuracy in prediction of lung cancer.

D. Abdullah *et. al.* [9] used the UCI repository for Lung Cancer dataset. They used three classifiers and compared their accuracy ratio. SVM (95.56%) outperformed K-nearest neighbor algorithm (KNN) (89.65%) and Convolutional Neural Network (CNN) (92.11%) in their experiment but KNN took minimum build time of 0.01 seconds.

P. Mohamed Shakeel *et al.* [10] proposed two methods for detection of lung cancer from CT images. The dataset used for this study was Cancer imaging Archive (CIA) dataset. Deep Learning trained neural network and Improved Profuse clustering were used in this study. CT images contained low quality images and it had noise, so to remove all this, CT image pre-processing was done. For improving the image quality, image histogram technique was used as it was a very efficient method on different images. Segmentation of cancer affected regions was done with the help of improved CT image using Image Pattern Correlation Technique (IPCT). The improved profuse clustering technique was applied to cancer influenced parts from the improved lung CT image. For detecting inconsistency in the image pixels, two procedures of improved profuse techniques worked as it checked the image pixel and put the similar super pixel in the same group. Predicting the similitude of data using the pixel eigenvalue was done during the process of segmentation when the pixels were continuously examined. Different features of spectral that are standard deviation, 3rd-moment skewness, mean, and 4th-moment kurtosis were derived from the region which are segmented and which was forwarded for the feature extraction stage as it was very effective to spot lung cancer which had connected features. 98.42% accuracy was ensured by the system with minimum classification error to be 0.038.

Few other researches have been mentioned in the comparative study in **Table 1** given below:

Table 1: Comparative study of researches in Lung Cancer prediction

Reference	Year	Dataset	Algorithm	Results
I. M. Nasser *et.al.* [11]	2019	UCL (Symptom dataset)	Artificial Neural Network (ANN)	Accuracy: 96.67%
W. Zhu *et. al.* [12]	2018	LUNA 16	3D Faster Region Based CNN	Accuracy: 81.42%
M. Nishio *et.al.* [13]	2018	The Cancer Imaging Archive	XGBoost	Accuracy: 79.7%
D. Moitra *el. al.* [14]	2020	The Cancer Imaging Archive	1D CNN	Accuracy: 96±3%
S. Makaju *et. al.* [15]	2017	LIDC-IDRI	SVM	Accuracy: 92%

2.2 Diabetes Mellitus

D. Sisodia *et. al*. [16] proposed a model to predict diabetes using various machine learning algorithms. They used classification algorithms, i.e., Naive Bayes (NB), Support Vector Machines (SVM) SVM, decision trees (DT) to predict disease at early stage on Pima Indian Diabetes Dataset. The results obtained were verified by Receiver Operating Characteristic (ROC) curves and showed that Naive Bayes gave 76.30%, highest accuracy of all of them.

Chen *et al*. [17] used boosting techniques, LogitBoost and AdaBoost to classify diabetes. The dataset belonged to Hospital of Wenzhou Medical University which had the medical records of patients from 2004 to 2014. They also used Random Forest and Logistic Regression techniques to test the clinical records but found that these two didn't perform well as the boosting algorithms. The results revealed that LogitBoost algorithm gave highest accuracy of 95.30%.

S.Ahuja *et.al*. [18] used ANN, Naive Bayes, Deep Learning (DL) and Decision Tree algorithms on Pima Dataset. All these algorithms achieved an accuracy in a range of 90-98% of which, Deep Learning algorithms gave the highest accuracy of 98.07%.

M. T. Islam *et al*. [19] studied a dataset of patients having diabetes which were categorized as Typical and Non-Typical. The dataset was obtained from Khulna Diabetes Hospital, Khulna which had 27 features and 340 instances. Pre-processing of data was done using inbuilt functions of WEKA 3.8 as well as 10-Fold Cross validation was done. The algorithms used were Bagging, Logistic Regression and Random Forest which gave 89.12%, 83.24% and 90.29% accuracy respectively.

S. Wei *et.al.* [20] performed the predictive analysis in four steps on the same Pima dataset. First, data pre-processing was done using two techniques, Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA). Then, parameter optimization was performed and comparison with techniques on basis of accuracy was done. They used Deep Neural Networks (DNN) and SVM algorithms of which, DNN gave the highest accuracy of 77.86%.

Comparative study of a few researches is shown below in **Table 2**

Table 2: Comparative study of researches in Diabetes Mellitus prediction

Reference	Year	Dataset	Algorithm	Results
M Chakradar *et. al*. [21]	2020	CALERIE dataset	Logistic Regression; XGBoost; SVM; LDA	Accuracy: 97±1(for all)
K. Kannadasan, *et.al*. [22]	2019	Pima Indian Dataset	DNN Stacked Auto Encoders	Accuracy: 86.26%
P. Juliet *et. al*. [23]	2019	Pima Indian Dataset	Naive Bayes Decision Tree K Star Logistic Regression; SVM	Precision: 0.770, Recall: 0.775; Precision: 0.742, Recall: 0.749; Precision: 0.691, Recall: 0.699; Precision: 0.772, Recall: 0.777; Precision: 0.767, Recall: 0.771;
S. Dey *et. al*. [24]	2018	Pima Indian Dataset	SVM + MMS KNN+ MMS GNG+MMS ANN+MMS (MMS= Min Max Scaler)	Accuracy: 78.05% Accuracy: 75.5% Accuracy:79.3% Accuracy: 82.35%
Mercaldo *et.al*. [25]	2017	Pima Indian Dataset	J48 MLP Hoeffding Tree JRip Bayes Net Random Forest	Precision: 0.742 Recall: 0.749 Precision: 0.752 Recall: 0.755 Precision: 0.770 Recall: 0.775 Precision: 0.755 Recall: 0.749 Precision: 0.749 Recall: 0.75 Precision: 0.743 Recall: 0.747
D. Pei *et.al.* [26]	2019	Chinese ethnic population	Decision Tree	Precision:94.0%, Recall:94.2%

2.3 Myocardial infarction

J. F. Wu *et al.* [27] developed a new deep feature learning method. They used Electrocardiography (ECG) datasets obtained from the Physikalisch-Technische Bundesanstalt (PTB) diagnostic database. The optimized features were fed into the SoftMax regression to build a multi-class classifier. Their approach had a specificity of 99.82% and sensitivity of 99.64%.

U. R. Acharya *et al.* [28] proposed a method to automatically diagnose MI using 11-layer deep CNN. The proposed model achieved an accuracy of 93.53% when tested with a dataset containing noise and an accuracy of 95.22% when tested with a dataset without noise. The paper suggested that the model was able to predict with high accuracy even when the ECG signals were noisy.

A. K. Dohare *et al.* [29] performed detection of MI using a 12-lead ECG system with support vector machine (SVM) classifier. The work has been performed using PTB diagnostic ECG database from physio bank as training dataset. Two hundred and twenty parameters were determined in the average beat of selecting 10 seconds data length in all 12-lead ECG. Applying above parameters with SVM classifier, an accuracy of 98.33% and sensitivity and specificity of 96.66% and 100% was achieved respectively.

M. Hammad *et al.* [30] proposed a method where they directly feed the ECG raw data directly to CNN model that classifies the signals into two classes, i.e., Normal or MI. In order to deal with the imbalance in data they have proposed a new method based on focal loss. Their method achieved an accuracy of 89.72% without using focal loss and 98.8% with using focal loss.

Comparative study of a few researches is shown in the **Table 3** below:

Table 3: Comparative study of researches in detection of myocardial infarction

Reference	Year	Dataset	Algorithm	Results
L Sharma *et. al.* [31]	2019	PTB database	Multi-channel CNN and LSTM	Accuracy: 95.4%
J. Zhang *et. al.* [32]	2019	PTB diagnostic ECG database	Staked Sparse autoencoders with TreeBagger	Accuracy: 99.90%
K. Feng *et. al.* [33]	2019	PTB diagnostic ECG database	Multi-channel CNN and LSTM	Accuracy: 95.4%
R. K. Tripathy *et. al.* [34]	2019	PTB diagnostic ECG database	Deep Layer Least Square SVM	Accuracy: 99.97%
L. Ibrahim, *et. al.* [35]	2020	ECG-VIEW II database	CNN RNN XGBoost	Accuracy: 89.9% Accuracy: 84.6% Accuracy: 97.5%

2.4 Brain Tumour

As per M. Soltaninejad [36], MRI was used to visualize internal body tissues that are used to examine brain tumor cells. In this paper, MRI segmentation was performed based on different algorithms and threshold methods. The segmentation method was used for the automatic identification of the position and boundaries of brain pathology in a highly efficient manner. The method can also be used to conduct a qualitative analysis of the brain area for the separation of tumor cells having high levels of sensitivity. The dataset used was taken from Multimodal Brain Tumor Image Segmentation Benchmark (BRATS) 2012 dataset. The average detection sensitivity, balanced error rate and the Dice overlap measure for the segmented tumor against the ground truth are 89.48 %, 6 % and 0.91, respectively.

As reported by M. Drozdzal *et al.* [37], tumor cells in the brain lead to cancer. Gliomas, which is a general brain tumor, causes death. Here, an automatic segmentation method was designed for the identification of gliomas using MRI. The method was more effective than the other method, as tumor cells were selected from the histogram and pixel intensity of the segmented region. The technique successfully detected brain tumors, and it provided effective performance with higher noise reduction and an accurate segmentation method. Based on this review of the relevant literature, it was concluded that under-segments and over-segments of brain tumor regions can be used to detect abnormalities. Automatic ROI detection is considered as a significant area of research in brain tumor detection and analysis.

As cited by W. Wang *et al.* [38], a study based on convolutional neural network which was combined with MRI detection technology to construct a model adapted to brain tumor feature detection. The main function of this research model was to segment and recognize MRI brain tumors and use convolutional layer to perform convolution operation to improve recognition efficiency and combine artificially selected features with machine learning features. The dataset used in this research was the GBM dataset. The experiment proved that using KECA for dimensionality reduction achieved a balance between time and precision. Here, the sample data in the high-dimensional space was projected into the low-dimensional space by linear transformation, thereby extracting the main features of the data in the original space and removing the correlation between the features.

N. Kesav *et al.* [39] proposed a novel architecture for Brain tumor classification and tumor type object detection using the RCNN technique which had been analyzed using two publicly available datasets from Figshare and Kaggle (2020). The aim was to decrease the execution time of a conventional RCNN architecture with the use of a low complex framework and propose a system for brain tumor analysis. The Two Channel CNN was used for a low complex architecture to classify between Glioma and healthy tumor MRI samples which was successfully done with an accuracy of 98.21%.

A. Rehman *et al.* [40] proposed a framework where they employed a setup called tri-architectural CNN (convolution neural network) for classification of tumours of different types (like AlexNet, GoogLeNetand VGGNet). The classification involved pituitary gland tumours, glioma tumours, and meningioma tumours types. The above-mentioned algorithm sliced the brain MRI to locate regions of interest. Freezing and fine tuning were applied to the sets of data for further classification. The authors also considered data augmentation techniques to obtain accuracy. The accuracy obtained by this research was 98.69% which was obtained by employing VGG16 (OxfordNet) architecture for enhancing detection and classification.

Comparative study of some more researches has been shown in **Table 4** below:

Table 4: Comparative study of researches in detection of Brain tumour

Reference	**Year**	**Dataset**	**Algorithm**	**Results**
K. Usman and K. Rajpoot [41]	2017	MICCAI BRATS data	Random Forest KNN AdaBoostM2 RusBust	Accuracy: 0.90 ± 0.03 Accuracy: 0.88 ± 0.03 Accuracy: 0.89 ± 0.03 Accuracy: 0.90 ± 0.02
A. R. Abdulraqeb *et. al.* [42]	2017	1. 12 images from Vladimir using a Philips Intera scanner with magnetic field induction of 1.5 T 2. 44 images from Riyadh, Saudi Arabia, using a GE Signa scanner with magnetic field induction of 1.5 T	Automated segmentation algorithm	Dice Coefficients: Dataset 1: 0.93 Dataset 2: 0.91 Sensitivity: 0.89 Specificity: 0.99
L. Lefkovits *et. al.* [43]	2017	BRATS dataset	Random Forest SVM Adaboost	Dice Coefficients: RF: WT- 0.905; TC-0.887 SVM: WT-0.736; TC-0.817 Adaboost: WT-0.720; TC 0.791
S. Deepak, P.M. Ameer [44]	2019	Figshare	InceptionV3(Transfer Learning)-Softmax	Accuracy: 99.4453%
A. Kabir *et. al.* [45]	2018	IXI dataset, Cancer imaging archive dataset, REMBRANDT dataset, TCGA-GBM data collection	CNN evolved with Generic algorithm	For glioma grades:90.9% For Glioma, Meningioma, and Pituitary tumor: 94.2%

III. CONCLUSION

From the literature survey and comparative study of every disease given in the previous section, some important facts and patterns were identified.

Researchers have used various deep learning algorithms for performing predictions on various datasets in case of lung cancer prediction which is appreciable. They must also consider the latest machine learning algorithms or ensemble techniques like LightBGM and XGBoost with the aim of improving the accuracy.

There are certain loop holes in the current diabetes prediction system. Most of the researchers have used the traditional PIMA Indian Diabetes Dataset which includes an attribute for number of pregnancies which means the dataset is centred around diabetes prediction in women. The dataset needs to be changed. There is a need to create a more generalized dataset where gender is also considered.

Several techniques had been presented in the field of myocardial infarction detection but achieving accuracy and computational complexity remains challenging tasks as we have surveyed that most of the researchers proposed their models using traditional ML algorithms like SVM, Decision trees, XGBoost, KNN, CNN, etc. as discussed in previous section. There are rarely any research works where a dataset other than PTB diagnostic ECG database is used. Hence, use of a different dataset and latest ML algorithms may improve the accuracy and lead to further research in this field.

From the survey of brain tumour researches, a good variety in machine learning algorithms and datasets is observed. Researches must be carried out to accelerate real-time medical applications and computation using machine learning techniques in the medical internet of things.

In conclusion, role of machine learning algorithms in disease prediction and detection has developed to a great extent recently. There is further scope of research in this field by considering real-time applications and involvement of new datasets and algorithms for improvement of accuracy.

IV. ACKNOWLEDGEMENT

We are grateful to Head of Department, Dr. N. F. Shaikh and entire Computer Engineering Department of Modern Education Society's College of Engineering, Pune for their constant guidance and support.

V. REFERENCES

[1] Top 10 Causes of Death Worldwide, Available at: https://www.aarp.org/health/conditions-treatments/info-2020/world-health-organization-data.html, accessed October, 2021.

[2] Beta Cells, Diabetes.co.uk: https://www.diabetes.co.uk/body/beta-cells.html, accessed October,2021.

[3] Diabetes mellitus, Britannica, Available at: https://www.britannica.com/science/diabetes-mellitus, accessed October,2021.

[4] Classification and Diagnosis of Diabetes, Available at: https://care.diabetesjournals.org , accessed October, 2021

[5] Diabetes Complications, Available: https://www.webmd.com/diabetes/diabetes-complications, Accessed October, 2021.

[6] WHO, Cardiovascular diseases., Available at: https://www.who.int/health-topics/cardiovascular-diseases/, accessed October, 2021

[7] A. Bankar, K. Padamwar and A. Jahagirdar, Symptom Analysis using a Machine Learning approach for Early-Stage Lung Cancer, *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, 2020, pp. 246-250.

[8] J. Alam, S. Alam and A. Hossan, Multi-Stage Lung Cancer Detection and Prediction Using Multi-class SVM Classifier, *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2),* 2018, 1-4, doi: 10.1109/IC4ME2.2018.8465593.

[9] Mustafa Abdullah, D., Mohsin Abdulazeez, A., & Bibo Sallow, A. Lung cancer Prediction and Classification based on Correlation Selection method Using Machine Learning Techniques. *Qubahan Academic Journal*, 1(2), 2021, 141–149.

[10] P. Mohamed Shakeel, M.A. Burhanuddin, Mohamad Ishak Desa, Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks, *Measurement,* 2019, https://doi.org/10.1016/j.measurement.2019.05.027

[11] I. M. Nasser and S. S. Abu-Naser, Lung Cancer Detection Using Artificial Neural Network. *International Journal of Engineering and Information Systems (IJEAIS)*, 2019, 17-23.

[12] W Zhu, C Liu, W Fan and X Xie, Deeplung: Deep 3d dual path nets for automated pulmonary nodule detection and classification, *IEEE Winter Conf. on Applications of Computer Vision (WACV)*, 2018, 673-681.

[13] M. Nishio, M. Nishizawa, O Sugiyama, R. Kojima, M Yakami, T. Kuroda, K Togashi, Computer-aided diagnosis of lung nodule using gradient tree boosting and Bayesian optimization, *PLoS One*, 2018, doi: 10.1371/journal.pone.0195875.

[14] D Moitra D and RK Mandal, Classification of Non-Small Cell Lung Cancer using One Dimensional Convolutional Neural Network, *2020 Expert Systems with Applications*, 2020, 113564.

[15] S Makaju, PW Prasad, A Alsadoon, AK Singh and A Elchouemi, Lung cancer detection using CT scan images, *Procedia Computer Science*, 2017 125.

[16] D. Sisodia, D.S. Sisodia, Prediction of Diabetes using Classification Algorithms, *International Conference on Computational Intelligence and Data Science (ICCIDS 2018)*, 2018, Vol. 132, pp. 1578-1585.

[17] P. Chen, C. Pan, Diabetes classification model based on boosting algorithms, *BMC Bioinformatics 19*, (2018). https://doi.org/10.1186/s12859-018-2090-9.

[18] S. Ahuja, H. Naz, Deep learning approach for diabetes prediction using PIMA Indian dataset. *Journal of Diabetes and Metabolic Disorders*, 2020. https://doi.org/10.1007/s40200-020-00520-5

[19] M. T. Islam, M. Raihan, F. Farzana, M. G. M. Raju and M. B. Hossain, An Empirical Study on Diabetes Mellitus Prediction for Typical and Non-Typical Cases using Machine Learning Approaches, *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, 2019, doi: 10.1109/ICCCNT45670.2019.8944528.

[20] S. Wei, X. Zhao and C. Miao, A comprehensive exploration to the machine learning techniques for diabetes identification, *2018 IEEE 4th World Forum on Internet of Things (WF-IoT),* 2018, doi: 10.1109/WF-IoT.2018.8355130.

[21] M. Chakradar, A. Aggarwal, A Machine Learning Based Approach for the Identification of Insulin Resistance with Non-Invasive Parameters using Homa-IR, *International Journal of Emerging Trends in Engineering Research*, 2020, 2055-2064.

[22] K. Kannadasan,et. al, Type 2 diabetes data classification using stacked autoencoders in deep neural networks, *Clinical Epidemiology and Global Health*, 2019, 530-535.

[23] P. Juliet, T. Bhavadharani, An Improved Prediction Model For Type 2 Diabetes Mellitus Disease Using Clustering And Classification Algorithms, *International Research Journal of Engineering and Technology (IRJET)*, 2019, 1179-1186.

[24] S. K. Dey, A. Hossain and M. M. Rahman, Implementation of a Web Application to Predict Diabetes Disease: An Approach Using Machine Learning Algorithm, *2018 21st International Conference of Computer and Information Technology (ICCIT)*, 2018, doi: 10.1109/ICCITECHN.2018.8631968.

[25] F. Mercaldo, et. al, Diabetes Mellitus Affected Patients Classification and Diagnosis through Machine Learning Techniques, *International Conference on Knowledge Based and Intelligent Information and Engineering Systems, KES2017*, 2017, 2519-2528, 2017.

[26] D.Pei, C.Zhang, et.al, Identification of Potential Type II Diabetes in a Chinese Population with a Sensitive Decision Tree Approach, *Journal of Diabetes Research*, 2019.

[27] J. F. Wu, Y. L. Bao, S. C. Chan, H. C. Wu, L. Zhang and X. G. Wei, Myocardial infarction detection and classification — A new multi-scale deep feature learning approach, *2016 IEEE International Conference on Digital Signal Processing (DSP)*, 2016, doi: 10.1109/ICDSP.2016.7868568.

[28] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, Application of deep convolutional neural network for automated detection of myocardial infarction using ecg signals, *Information Sciences*, 2017, 190–198.

[29] A. K. Dohare, V. Kumar, and R. Kumar, "Detection of myocardial infarction in 12 lead ecg using support vector machine," *Applied Soft Computing*, 2018, 138–147.

[30] M. Hammad, M.H. Alkinani, B. B. Gupta, Myocardial infarction detection based on deep neural network on imbalanced data., *Multimedia Systems*, 2021, https://doi.org/10.1007/s00530-020-00728-8.

[31] L. Sharma, Dev, Sunkaria, and R. Kumar, Inferior myocardial infarction detection using stationary wavelet transform and machine learning approach, *Signal, Image and Video Processing*, 2018, 199–206.

[32] J. Zhang, F. Lin, P. Xiong, H. Du, H. Zhang, M. Liu, Z. Hou, and X. Liu, Automated detection and localization of myocardial infarction with staked sparse autoencoder and treebagger, *IEEE Access*, 2019, 70634–70642.

[33] K. Feng, X. Pi, H. Liu, K. Sun, Myocardial infarction classification based on convolutional neural network and recurrent neural network. *Appl. Sci*, 2019, 1879.

[34] R. K. Tripathy, A. Bhattacharyya, R. B. Pachori, A novel approach for detection of myocardial infarction from ECG signals of multiple electrodes, *IEEE Sens. J*. 2019, 4509–4517.

[35] L. Ibrahim, M. Mesinovic, K. W. Yang and M. A. Eid, Explainable Prediction of Acute Myocardial Infarction Using Machine Learning and Shapley Values, *IEEE Access*, 2020, 210410-210417, doi: 10.1109/ACCESS.2020.3040166.

[36] M. Soltaninejad, Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in flair mri, *Int. J. Comput. Assist. Radiol. Surg*, 2017, 183–203

[37] M. Drozdzal et al., Learning normalized inputs for iterative estimation in medical image segmentation, *Med. Image Anal*, 2018, 1-13.

[38] W. Wang, F. Bu, Z. Lin and S. Zhai, Learning Methods of Convolutional Neural Network Combined with Image Feature Extraction in Brain Tumor Detection, *IEEE Acces*, 2020, doi: 10.1109/ACCESS.2020.3016282

[39] N. Kesav, M.G. Jibukumar, Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN, *Journal of King Saud University - Computer and Information Sciences*, 2021, https://doi.org/10.1016/j.jksuci.2021.05.008.

[40] A. Rehman, S. Naz, M. I. Razzak, F. Akram and M. Imran, A deep learning-based framework for automatic brain tumors classification using transfer learning, *Circuits Syst. Signal Process*., 2019, 757-775.

[41] K. Usman and K. Rajpoot, Brain tumor classification from multi-modality mri using wavelets and machine learning, *Pattern Anal. Appl*, 2017, 871–881.

[42] A.R.Abdulraqeb, W. Al-Haidri, L.T.Sushkova, M. Abounassif, P. Parameaswari, and M. Muteb, An automated method for segmenting brain tumors on mri images, *Biomed. Eng*, 2017, 97–101.

[43] L.Lefkovits, S. Lefkovits, M. Vaida, S. Emerich, and R. Malut, Comparison of classifiers for brain tumor segmentation, *International Conference on Advancements of Medicine and Health Care through Technology*; 2017.

[44] S. Deepak, P.M. Ameer, Brain tumor classification using deep CNN features via transfer learning, *Computers in Biology and Medicine*, 2019, https://doi.org/10.1016/j.compbiomed.2019.103345.

[45] Amin Kabir Anaraki, Moosa Ayati, Foad Kazemi, Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms, *Biocybernetics and Biomedical Engineering*, 2019, https://doi.org/10.1016/j.bbe.2018.10.004