ISSN 2278-3091
Volume 9, No.5, September - October 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse105952020.pdf
https://doi.org/10.30534/ijatcse/2020/105952020

Multi-Classification for Cardiac Arrhythmia Detection using Deep Learning

S. Komal Kour[1] , Dr. T.Adilakshmi[2]
[1]Department of CSE, Vasavi College of Engineering, Telangana, India, komalkour@staff.vce.ac.in
[2] Department of CSE, Vasavi College of Engineering, Telangana, India, t_adilakshmi@staff.vce.ac.in

ABSTRACT

Cardiac Arrhythmias are any of a bunch of conditions within which the electrical activity of the guts is irregular or is quicker or slower than normal. It is the leading reason for death for men and women within the world. Electrocardiogram (ECG or EKG) is the most generally used first-line clinical tool for checking electrical activity within the heart. Using ECG recordings to automatically identify arrhythmia accurately and efficiently and it is very important tool for Cardiologists. It is also one in all the primary line tests which is employed to test for problems with electrical activity of the muscles of cardiac patients. ECG data is performed as a part of a physical activity, making its use for detection of heart abnormalities. Hence, accurately predict the cardiac arrhythmia using ECG data of the patient. Proposed system uses the MIT BIH arrhythmia data set to implement a multinomial classification for various sorts of heart abnormalities using the Convolutional Neural Network (CNN) Model of Deep Learning.

Key words: Deep Learning, Multinomial Classification, ECG, Cardiac arrhythmias.

1. INTRODUCTION

The cardiac arrhythmia is the leading on-going disease which is usually seen in people around irrespective of the age of the person. Irregularity in heartbeat leads to the occurrence of arrhythmia, around 2-3 lakhs of sudden deaths occur every year which is higher than the people facing death with lung or breast cancers. According to National Centre for Biotechnology Information (NCBI), arrhythmia is the most public health problem across the globe. Arrhythmia accounts 15 - 20% of the death that is happening daily across the globe. Early defibrillation will help the people to survive but in most of the cases implementations and processing are slow and that is the main reason why the death percentage is 15-20% of death counting each day. These types of diseases need an immediate action to take and if not, they may lead to end up their life. To maintain a track on the regularity or irregularity of heartbeat and to overcome the cardiac arrhythmia (fluctuations in heart beats) ECG data is taken, processed and the status of the arrhythmia is confirmed. Cardiac arrhythmia can be caused because of alcohol abuse, diabetes, stress, smoking, heart disease like congestive heart failure etc. These are some of the reasons for an individual getting cardiac arrhythmia. There are different kinds of cardiac arrhythmia like Atrial fibrillation which is generally developed in adults of 65 years age, atrial flutter which is faced when one of the atrium is not conducting properly, supra ventricular tachycardia which is rapid regularity in heartbeat etc. These are some of the type of cardiac arrhythmias that a person or an individual may affect in their daily life.

To overcome these types of health issues bringing out the new technology may help in detecting the early stages of cardiac arrhythmia and in further classification in the cardiac arrhythmia it may add as a plus point for an individual to save a life. Our project enables or provides a better way of management or discovering weather the person is having cardiac arrhythmia or not and further conducts the classification of the cardiac arrhythmia.

ECG is electrocardiogram which is generally used to measure the heartbeat rate and generate the signals which are composed of waves. If the heartbeat is fast it is considered as Tachycardia and slow heartbeat is classified as brady cardia which will be useful for a person to take care of his/her health conditions. An ECG signal is composed with waves which represent the electrical potentials of the heartbeat with electrodes placed on the chest and limbs. These collect the heartbeat movements and shows in forms of waves.

In many of the domains the cardiac arrhythmia is determined with time, frequency domain and frequency-time domain techniques without removing the external and internal noises which generates an inappropriate condition on the human arrhythmia. The complex of the QRS which are generated by the ECG signals varies with the conduction path of the activated pulse. Features are extracted from heartbeat to detect arrhythmia waveform. By this extracted arrhythmia waveform, the parameters of amplitude, duration parameters and combined parameters are taken and rationalized to the arrhythmia status, but this cannot be accepted as a justified solution because the noise may change the waveform which are generated by the ECG.

For the Detection of Cardiac arrhythmia, the heartbeat data of human is taken from ECG, initially it is processed by removing the noises, then the signals are converted into images and the peaks are calculated. If the interval of the peaks is more it is considered as slow, then it is bradycardia else it is considered as tachycardia. It is predictable whether it is bradycardia or tachycardia.

2. RELATED WORK

In the existing system the data for building the model is taken from MIT-BIH dataset. Here the pre-processing of signals is done to remove the base line, power line, low frequency noise and the high frequency noises present in the dataset for more accurate results. After pre-processing the extraction of the features is done by using a Convolutional neural network. Although the recognition of pattern techniques have applied to the arrhythmia detection tasks using ECG, very challenging to implement these techniques to the field of medical image and signal processing. The input can be 1D, 2D…… nD, but in the existing system the inputs are only 1D so the model which their build will give outputs to only such signals. The QRS peak is detected but there are no segmentations of heartbeats is done. Here the signals are processed for building a model. The number of clusters formed here are very few.

There are few disadvantages in the existing system such as we can only use the 1D signal in the existing system. If the signals are other than the 1D then the system will not give any output. There is no segmentation of heart beats i.e. segmentation is a way of arranging into distinct sub groups that typically have separate needs. Only QRS peak is detected in the system. Unlike in the proposed system will not have conversion of images in the existing system. In the existing system can only say that whether the patient has the disease or not, can only form few clusters.

2.1 Literature Survey

Sivanantham and S. Shenbaga Devi proposed that the ECG signals from the MIT BIH dataset are to be pre-processed using a bandpass filter, then the QRS segment or peak in the signal is detected using the Hamilton and Pan Tompkins Algorithm. The feature extraction is based on heart rate variability (HRV) signals by extracting different features in the time domain, frequency domain and nonlinear features from HRV signals, the extracted features are fed into a Support Vector Machine to carry out the final classification.

Kyungna Kim explored deep neural networks for the task of ECG recordings classification. He used the dataset of 106 patients. He categorized the slices of ECG data into 6 classes. The data used to train the models is a set of ECG recordings, obtained from UCSF. Long short-term memory units are used to build recurrent neural networks. Recall, precision, f1 score are used as performance metrics. They used various layer unidirectional and bidirectional LSTM to get the effectiveness of combining the residual connections.

Munya A. Arasi , Sangita babu [21] did survey of Machine Learning Techniques like Decision Tree, Support Vector Machines in Medical Imaging such as Brain tumor classification, Breast cancer prediction and also lung cancer diagnoising.

Ali Isin and SelenOzdalili developed a model in which the ECG signals from the MIT BIH dataset are pre-processed to remove dc noise and power line interference, then the QRS segment or peak in the signal is detected using the Pan Tompkins Algorithm. Then the signals are converted to images, and the images are fed to a framework called a deep learning previously trained on a data set of general images to carry out automatic arrhythmia diagnostics using ECG. Feature are extracted and fed into neural network back propagation method for the classification precision.

Anake Pomprapa[14] developed a combination of feature extraction and a supervised learning algorithm using CNN for the classification of arrhythmia. The ECG signals from the MIT BIH dataset are denoised and filtered to remove dc noise and power line interference, then the QRS segment or peak in the signal is detected using the Biorthogonal Wavelet Filter. The features are extracted and classified using a deep learning model that constitutes CNN.

A. Rajkumar and M. Ganesan [16] proposed to utilize a Convolutional Neural System (CNN) a Deep Learning calculation which is proficient in characterizing signals. Using CNN, highlights are found out Naturally from the time space ECG signals. The signs are gained from the MIT-BIH database. The CNN is prepared, tried utilizing ECG Dataset gotten from MIT-BIH Database and from the sign 7 sorts of arrhythmia were arranged. There is no pre- handling done by the creators and the CNN is prepared utilizing Stochastic Slope Descent calculation.

Dr. Navneet Malik , Vinod B Bharat, Sudhanshu P Tiwari and Jimmy Singla [22] has surveyed on medical imaging using Deep Learning techniques. Different types of cancer like brain cancer, lung cancer, skin cancer prediction using the Convolutional Neural Network, Deep Belief Network.

K.S. Rajput and S. Wibowo have done Pre-Processing of ECG data on raw ECG signals to removes noise. It is done through notched filters, bandpass filters, and adaptive filters. The method splits the signal of ECG into segments. 2D feature images are represented from 1D segments based on wavelets or Fourier transform. They have used CNN for classification and for ECG visualization they used Bio fourmis web application and the ECG visuals are compared with the healthy ECG data and the arrhythmia is decided.

Miquel Alfaras and Miguel C. Soriano have performed many classification algorithms that are assessed using four standard statistical measures: sensitivity, positive predictive value, specificity, and accuracy. They are calculated by processing the ECG data by ECG re-sampling, ECG filtering, Heartbeat detection, RR calculation, Heartbeat segmentation and Heartbeat normalization. The classification is done by using the Echo State Network (ENS) with ring topology. This classified data is compared with a healthy heartbeat classified data and Arrhythmia is detected.

3. PROPOSED METHOD

In the model which assembled information is taken from MIT-BIH dataset. The first step is to pre-process the signs to expel the gauge, power line, low recurrence and high recurrence commotions present in the dataset. At that point the division of signs into heart pulsates is finished by distinguishing the QRS top and the R-R interim. QRS complex is the most striking waveform inside the ECG. Since it mirrors the electrical movement inside the heart during the ventricular withdrawal, the hour of its event just as its shape give significant data about the current condition of the heart. A notable Pan- Tompkins calculation is applied to convey out the QRS recognition. The calculation incorporates a progression of strategies that perform subordinate, figuring out, mix, versatile thresholding and look strategies for the recognition of R-pinnacles of the ECG signal. The pulses are changed over into pictures utilizing OpenCV and Matplotlib libraries of python language. The component extraction is finished by the convolutional neural system which follows the VGG Net engineering.VGG network model is similar to convolutional layers of 3×3 pile up over one another in increasing depth. Lowering volume size is dealt with by max pooling. Two associated layers, each with 4,096 hubs are at that point followed by a delicate max classifier. The arrangement is finished by utilizing extraordinary MLP Classifiers, LSTM, Faster RCNN and so forth.

The input can be 1D,2D……. nD so any type of inputs can be given into the system for getting the outputs. Segmentation of heart beat in the proposed system i.e. segmentation is a way of arranging into distinct sub groups that typically have separate needs. Heart beats are converted into images and detect QRS peak and also R-R interval. System can have many numbers of clusters such that it can identify the condition of the patient precisely. If the accuracy is less, then the architecture is changed automatically and calculated again. This process is done until it get the better accuracy. Hence the proposed system has wide range of advantages while compared to the existing system.

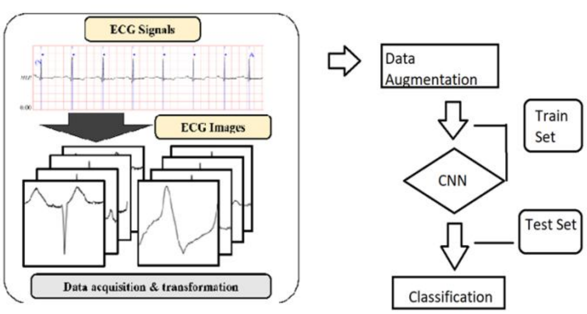

Figure 1: Architecture of Multi Classification of Cardiac Arrhythmia

4. IMPLEMENTATION

Firstly, Data is obtained from database of MIT-BIH. MIT-BIH dataset is online database is a set of over 400 long term ECG Holter recordings. For data acquisition, the segmentation method is used to separate the beats of each category. This method is used to categorize the heart beats into seven different categories. In Fig 2, it shows the classification of ECG Beats to various classes. They are APC (Atrial Premature Contraction), Normal, LBB (Left Bundle Branch Block), PAB (Paced Beat), PVC (Premature Ventricular Contraction), RBB (Right Bundle Branch Block) and VEB (Ventricular Escape Beat).

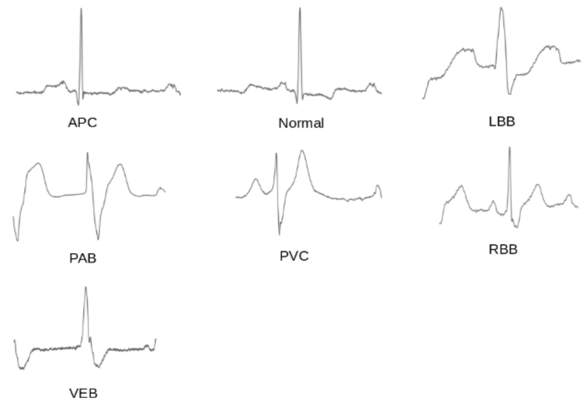

Figure 2: Segmented ECG beats of each class converted into images

CNN model takes image as input data, ECG Signals are Converted to ECG images in ECG Data pre-processing step by plotting each ECG beat. Firstly, Detection of R-peaks using BioSPPy python module. In Fig 4, A 7-layer architecture of CNN model is used which is similar to VGGNet. Each Layer includes the convolution layer which is used to extracts features from the input and followed by Rectified linear unit (RELU) which acts as an activation function and then followed by Batch Normalization. Batch Normalization that is B Norm offers a greater accuracy and better learning with parameters and computations. Every consecutive layers max pooling component is applied to reduce the dimensionality. And finally in the dense layer, neurons are fully connected followed by, RELU, B-Norm, dropout is used to drop the neurons to avoid over fitting and lastly applied Softmax to produce the multi classification for cardiac arrhythmia.

The Rectified Linear Unit (**ReLu)** is a linear function that gives the resultant as input directly if it is positive number, otherwise, it will resultant as zero. ReLu is often used function of activation for many of neural networks because a model that uses it is easier to train and often achieves better performance. The rectified linear activation function removes the problem of the vanishing gradient, allowing network to perform better.

$$g(z) = \max\{0, z\}$$

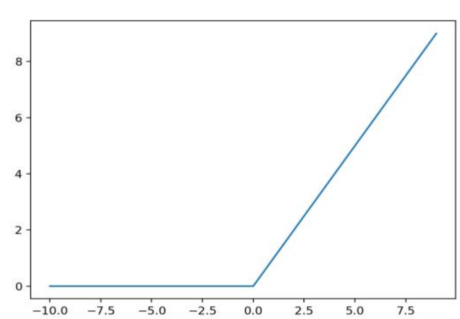

Figure 3 : Rectified Linear Unit

Batch Normalization

The concept of Batch Normalization, which in effect, normalizes the output activations that is ReLU.

$$Y_i = BN_{\Upsilon}(x_i)$$

The above equation describes what a batch norm layer does. A batch normalization layer helps our optimization algorithm to control the mean and the variance of the output of the layer.

Softmax

The multi class logistic regression uses the concept of the softmax function and it is sometimes called the soft argmax function. The generalization of logistic regression is softmax function and can be used for classification of multi class. The softmax function can be used in a classifier only when the classes are mutually exclusive. The formula of softmax is as follows along with each description of the component:

$$\sigma(Z_i) = e^{zi} / \sum_{J=1}^{K} e^{zj}$$

$\vec{z}$	The input vector to the softmax function, made up of (z0, ... zK)
z_i	All the zi values are the elements of the input vector to the softmax function, and they can take any real value, positive, zero or negative. For example a neural network could have output a vector such as (-0.62, 8.12, 2.53), which is not a valid probability distribution, hence why the softmax would be necessary.
e^{z_i}	The standard exponential function is applied to each element of the input vector. This gives a positive value above 0, which will be very small if the input was negative, and very large if the input was large. However, it is still not fixed in the range (0, 1) which is what is required of a probability.
$\sum_{j=1}^{K} e^{z_j}$	The term on the bottom of the formula is the normalization term. It ensures that all the output values of the function will sum to 1 and each be in the range (0, 1), thus constituting a valid probability distribution.
K	The number of classes in the multi-class classifier.

By using get records, downloaded the data from MIT-BIH dataset and then transformed ECG Signals to Images, have used Matplotlib and OpenCV. The segmented ECG Signals are converted into grayscale images. The segmented method is used to categorize the heart beats into seven different categories. Firstly,detected R-peaks using BioSPPy python module. This Module shows the R-Peak detection of each beat. Then, Augmented the data by cropping different sections of the image to the size of 96*96. After Preprocessing the data is feeded to Model.

Using CNN, train the model to predict the different classes based upon the input. First, the input data is passed to CNN Model, it can able to detect the class it belongs to and has shown one sample of ECG signal feed in the model, gets the range of samples classified according to cardiac condition in the Table 1. The dataset split the model to train and test is 85% and 15%. For each beat it gets the class it belongs to range and model got 92% of prediction in multi-classification of cardiac arrhythmia.

5. CONCLUSION

Via robotizing this it is significantly more supportive for the cardiologists, empowering them to concentrate more on treatment rather than diagnostics. Right-now proficient Convolutional Neural system is utilized for the ECG characterization. ECG characterization framework is acknowledged to do programmed ECG arrhythmia diagnostics by characterizing persistent ECG's.

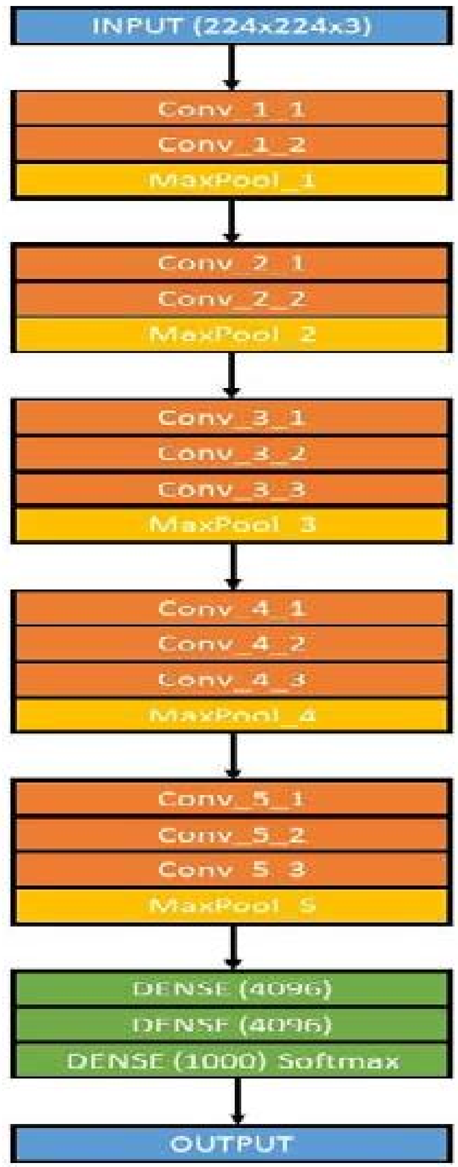

Figure 4: Architecture of CNN Model

Table 1: Output Target Representations

Cardiac Condition	Range
1. PVC	[430, 706]
2. Normal	[240,431]
3. VBB	[0,0]
4. RBB	[0,0]
5. PAB	[0,0]
6. APC	[0,0]

From the records of ECG from the MIT BIH database store, they are pre-handled or separated by utilizing dishTompkins calculation. This pre- handling helps in decreasing the clamour information. QRS waves are distinguished for the extraction of R-T sections of the ECG. By utilizing the OpenCV which is a python library the signs are changed over into pictures. Effectively prepared ResNet, is moved also, utilized as a component extractor for the ECG order. These separated highlights are encouraged into a back proliferation neural system to group the information ECG R-T portions into any one referenced condition. Moving a prepared profound convolutional neural system disposes of the requirement for mastery and computational force required for preparing a profound convolutional neural organize without any preparation. With the ongoing exhibitions of profound learn based restorative picture and sign handling strategies, biomedical researchers are one step nearer to PC upheld demonstrative framework.

6. Future Scope

Automatic heartbeat classification is essential for real-time applications in detection of cardiac arrhythmias. Programmed heartbeat order is basic for continuous applications in the location of cardiovascular arrhythmias. The acquired consequences of this proposal recommend that there is a potential development of future in programmed ECG order frameworks. The frameworks must incorporate four conclusive advances: pre-handling, QRS complex discovery, highlights extraction and order of pulses. The further exertion of this work should move towards proposing new component extraction and arrangement strategies.

The future is using this detection of cardiac arrhythmia tools in wearable devices so that they could continuously monitor the health of the person and send alerts when there is an abnormality. We additionally recommend the utilization of new patterns to catch the ECG signal, for example, off-the-individual methodologies, for the elaboration of new databases. In any case, we accept that the making of such databases would be an extraordinary test in light of the fact that, other than the money related costs included, they would need to be consolidated into gauges, for example, AAMI measures to contact the ideal crowd.

7. ACKNOWLWDGEMENT

Authors would like to express gratitude towards Vasavi College of Engineering, Hyderabad for their constant supervision as well as for providing necessary information regarding this research and also their support in completing this endeavor.

REFERENCES

1. Saman Parvaneha, Jonathan Rubina, Saeed Babaeizadehb Minnan Xu-Wilsona, ” **Cardiac arrhythmia detection using deep learning: A review**” Journal of Electrocardiology 2019.
2. C.K. Roopa and B.S. Harish, “**A Survey on various Machine Learning Approaches for ECG Analysis**” (IJCA) 2017.
3. Ali Isin, and Selen O zdalili, “**Cardiac arrhythmia detection using deep learning**” (ICSCCW) 2017.
4. Elif IZCI, Mehmet Akif OZDEMIR, Murside DEGIRMENCI and Aydin AKAN,” **Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique** “(IEEE) 2019.
5. A. Sivanantham and S. Shenbaga Devi, “**Cardiac Arrhythmia Detection using Linear and Nonlinear Features of HRV Signal**” (lCACCCT) 2014.
6. Victor Hugo C. de Albuquerque, Thiago M Nunes Danillo R Pereira,” **Robust automated cardiac arrhythmia detection in ECG beat signals** “ (NCAF) 2016.
7. Giovanna, Sannino& Giuseppe, De Pietro, “**A deep learning approach for ECG-based heartbeat Classification for arrhythmia detection** “(ELSEVIER) 2018.
8. Jer ́ome Van Zaen, Olivier Ch etelat, Mathieu Lemay, Enric M. Calvo and Ricard Delgado-Gonzalo, “**Classification of cardiac arrhythmia from single lead ECG with a convolutional recurrent neural network** “ (MQTT) 2018.
9. Xin Gao,” **Diagnosing Abnormal Electrocardiogram (ECG) via Deep Learning** “(IntechOpen) 2019.
10. Niharika Pattanaik, Ipsita Mohapatra, Mihir Narayan Mohanty, “**Arrhythmia detection using deep learning** “ (IJET) 2018.
11. Philip Warrick and Masun Nabhan Homsi, ”**Cardiac Arrhythmia Detection from ECG Combining Convolutional and Long Short-Term Memory Networks** “ (IEEE) 2017.
12. Pooja sharma, D.V Gupta, Surender Jangra, “**ECG Signal Based Arrhythmia Detection System Using Optimized Hybrid Classifier** “(IJITEE) 2019.
13. S. Celin and K. Vasanth, “**Survey on the methods for Detecting Arrhythmias using heart rate signals**” (JPSR) 2017.
14. Anake Pomprapa, Waqar Ahmed, André Stollenwerk, Stefan Kowalewski and Steffen Leonhardt, “**Deep Learning of Arrhythmia Analysis Based on Convolutional Neural Network** “ (IJBEM) 2019.

15. Yinsheng Ji, Sen Zhang and Wendong Xiao,"**Electrocardiogram Classification Based on Faster Regions with Convolutional Neural Network**"(MDPI) 2019.
16. Rajkumar. A, Ganesan. M, Lavanya. R, "**Arrhythmia classification on ECG using Deep Learning** "(ICACCS) 2019.
17. B Pyakillya, N Kazachenko, N Mikhailovsky, "**Deep Learning for ECG Classification**" (JOP) 2017.
18. Faizal Mahananto, TomohikoIgasaki, Nobuki Murayama, "**Cardiac Arrhythmia Detection using Combination of Heart Rate Variability Analyses and PUCK Analysis**" (IEEE EMBS) 2013.
19. Abawajy, J.H., Kelarev, A.V., Chowdhury, **"Multistage approach for clustering and classification of ECG data"**. Computer Methods and Programs in Biomedicine 112, 720–730 (2013)
20. All`ene, C., Audibert, J.Y., Couprie, M., Keriven, R.: **Some links between extremum spanning forests, watersheds and min-cuts**. Image and Vision Computing 28(10), 1460–1471 (2010)
21. Munya A. Arasi , Sangita babu "**Survey of Machine Learning Techniques in Medical Imaging**" (IJATCSE 2019).
22. Dr. Navneet Malik , Vinod B Bharat, Sudhanshu P Tiwari and Jimmy Singla "**Study of Detection of Various types of Cancers by using Deep Learning: A Survey**"(IJATCSE 2019).