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Deep-Neural Networks As Feature Extractors And Monolithic Neural Networks As Classifiers, For Classification Of Uterine Cervix Cancer Cases

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Abstract:-
With the advent of deep neural networks, application of machine learning in multidisciplinary problems enhanced many folds. Many unsolvable problems previously sought as complex to compute are now made solvable by deep neural network techniques. Problems like protein folding by Alpha-fold and Alpha-Go are prime examples. In this study six well known convolution neural networks are applied for the classification of uterine cervix cancer cases for both seven class and two class classification. A primary dataset was also created by collecting raw slide samples form the leading medical institutes. The machine learning techniques do require set of well-crafted feature values representing the ground truth. Many times, these features fail to represent the ground truth. The deep neural networks can extract all the relevant features itself and those extracted features are used for final classification. In this work the convolution neural networks are used for extraction of features which are the used for training shallow neural networks. The shallow neural networks used are Levenberg Marquardt neural network, One Step Secant and Scaled Conjugate gradient descent. The results indicated that among the 6 convolution neural networks the ResNet50 is best and among the three shallow neural network Levenberg Marquardt is best for both seven and two class classification. The duo (ResNet50 and Levenberg Marquardt) produced a classification accuracy of 82.92%. Among all the classes of diagnosis, class 7 has the best F-value followed by class 1, whereas class 4 has the lowest F- value followed by class 5 and class 2. Lowest F-value indicates maximum misclassification. For two-class classification, duo (ResNet50 and Levenberg Marquardt) produced classification accuracy is 94.77%. The F-value of both the classes is above 92% for all the combination of CNN and shallow neural network. The results do conclude that the deep neural networks can easily classify the cases of cervical cancer with notable accuracy, without feature extraction.

Keyword: Deep Neural Network, AI, Cervical Cancer,

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1. Introduction:-

1.1. Deep Neural Network

The conventional supervised machine learning algorithms uses lot of training data to develop

2. Selecting the most and appropriate number of discriminative features

se steps are the basis of many available automated medical image analysis tools. The extraction of relevant features still needs human intervention and these features are called hand crafted features. Extracting the most relevant and discriminative feature by the feature extraction step eases the feature selection and classification steps. Extraction of effective feature set is a complex task and often employs a series of image processing steps. These image processing steps are usually applied for segmentation of image into different segments corresponding to various region of interests and image decomposition. one of the main limitations and shortcomings of the conventional machine learning approach is the extraction of most relevant feature set. A classifier cannot learn the input space until and unless it is provided relevant feature-set along with adequate number of instances. With the advent of efficient processing units, algorithms are designed which enabled a computer to extract feature by itself without any human intervention. This concept forms the basis of *deep learning* also known as deep neural networks. These deep learning algorithms have several advantages over the conventional machine learning algorithms. A single deep learning architecture can perform all the three steps involved in conventional machine learning systems. The neurons of deep neural networks are able to extract the most discriminative feature from the input image. These neurons crafted features can compensate and can even surpass the conventional feature extraction algorithms. Finally, the feature set so created

an automated computer aided diagnostic system. These systems follow three important steps:

1. Extraction of feature from the ground truth

3. Training a statistical classifier All the

will be used to train the classifier layer of deep learning architecture. With such a design, the generalization error can be reduced more easily in a very systematic manner.

1.2. Deep Learning/Deep Neural Networks

Deep learning (DL) is a type of artificial intelligence technique that mimics how people acquire knowledge. It is a subset of machine learning and named as deep learning as it uses deep neural networks. It is an important field in Data Science that includes statistics and predictive modelling. Since the compilation, review and interpretation of large amounts of data are of enormous value to data scientists; deep learning techniques make this process faster and easier. Deep learning-based networks can automatically learn, without predefined knowledge explicitly coded by the programmers.

Fig.1. Steps in Deep Learning

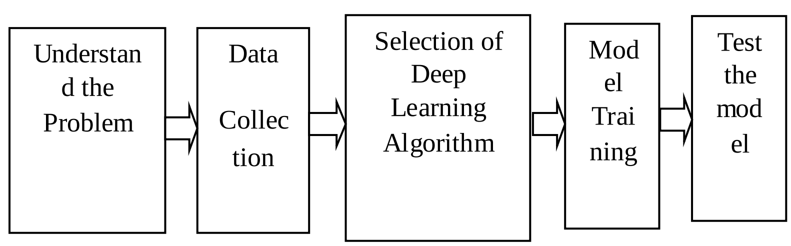

Fig. 1 represents the steps involved in deep learning. It involves understanding the problem to be solved and collect the data concerned with the selected problem under study. The next step deals with selection of appropriate deep learning model based on problem domain; followed by splitting the collected data into train set and test set. After this, model training gets started using train set. Finally model validation is performed using test set based on parameters obtained from confusion matrix.

The fig. 2 represents a general framework for deep learning architecture. The first layer (L_1) represents the input layer; the last layer (L_i) refers to the output layer and all the layers (from L_2 to L_{i-1}) in between are called as hidden layers consisting of neurons connected to each other.

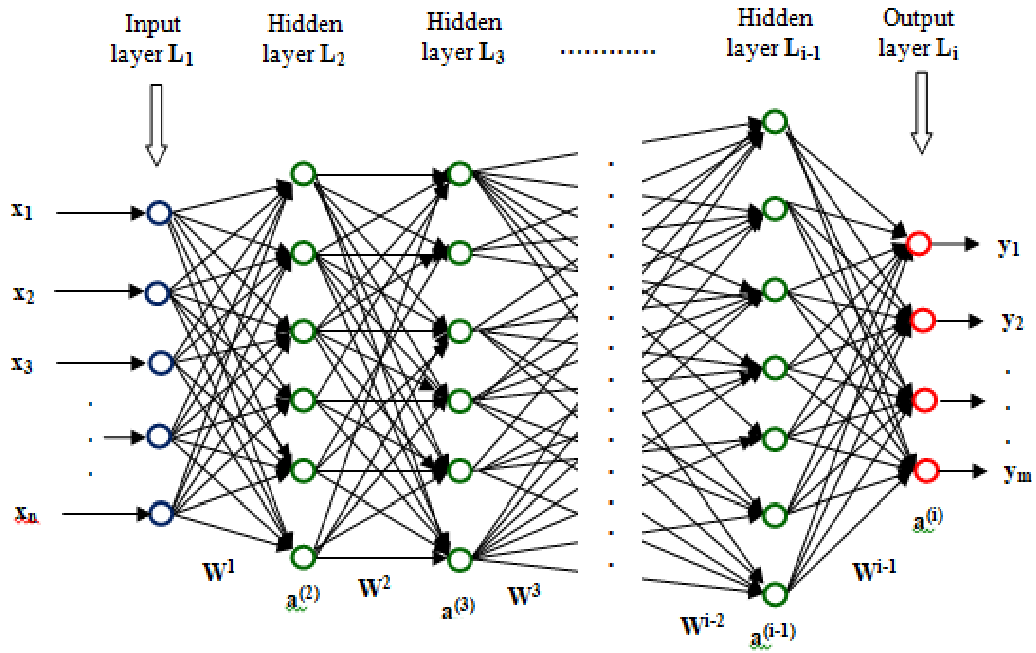

Fig. 2 General Architecture of Deep Neural Networks

The term *deep* represents more than two layers of the network joining neurons. In hidden layers, each neuron processes and then propagates the input signal obtained from the layer above it and the strength of the propagated signal depends on the weight of the neuron, activation function and bias value. Such networks take huge amounts of input data and work by operating them across multiple layers and the network subsequently learns complex features of the data at each layer.

Weight: Weight signifies how much the feature matters in the model and indicates how much evidence it offers for or against the current hypothesis in relation to the presence or absence of the pattern to be determined in the given input.

Activation Function: Activation function transforms the input data into a particular limited range that makes trained model more stable and efficient. The most widely used activation functions implemented in deep neural networks include *sigmoid*, *softmax*, *tanh*, *ReLU* (rectified linear units), etc.

Bias: Bias term refers to the constant added to the weighted input before the activation function to be applied. It only affects the output values; not interfering with the real input data and does not depend on previous layers' outputs.

1.3. Convolutional Neural Network (Cnn/Convnet) :

A convolutional neural network is a deep learning technique in which a learning model carries out classification from image, video, text, or sound data into their respective classes. It directly learns from the image data by mining patterns in order to classify images thereby eliminating the requirement of manual feature extraction and features are directly learned. It can give state-of-the-art recognition results or can be retrained for new tasks, enabling pre-trained model to be reused. CNN consists of tens or hundreds of layers in a way that each layer learns to identify different features in the given input image. Filters at different resolutions; are applied to each training image, and then the output of each convolved image is fed as the input to the succeeding layer.

1.3.1. Cnn Architecture

CNN mainly deals with the input in the form of image data and accordingly its architecture is implemented in order to deal with the specific type of data. CNN model can be built from scratch, or utilize a pre-trained model with new dataset on the basis of application domain. CNN mainly consists of three types of layers- convolutional layers, pooling layers and fully-connected layers. CNN architecture is shown in fig. 3. CNN architecture is implemented by stacking theses layers and presented in following figure.

1. *Input layer*: It holds the pixel values of the image.

2. *Convolutional layer*: It determines the output of neurons connected to local regions of the input by computing the scalar product between their weights and the region connected to the input volume. It applies a series of convolutional filters to the input images in order to extract specific features from the images. CNN performs convolution operation by filtering the image of size n*n with kernel of size f*f and stride length of s in order to produce feature map of size$\left(\frac{n-f}{s}+1\right)*\left(\frac{n-f}{s}+1\right)$.

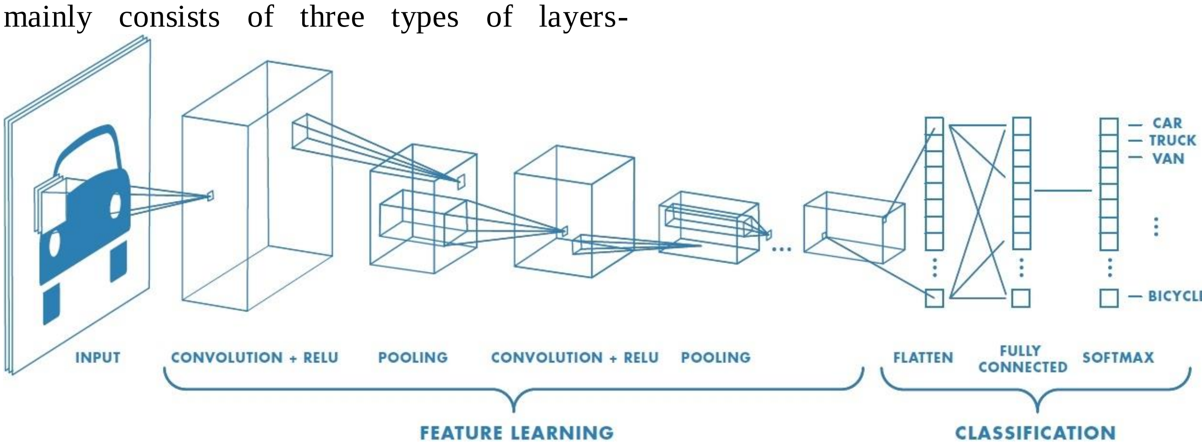

Fig. 3 General Architecture of CNN (https://towardsdatascience.com)

3. *Pooling layer*: It decreases the spatial dimensionality of the Convolved Feature in order to reduce the number of parameters within that activation, thus reducing computational power needed for processing the data using dimensionality reduction. It can also extract dominant features that are invariant to rotation and position, thereby generating effective trained model. There are mainly two types of pooling operation:

- Average Pooling: It returns the average of all the pixel values from the segment of the image enclosed by the Kernel.
- Max Pooling: It returns the highest pixel value from the segment of the image enclosed by the Kernel. It can also carry out Noise Suppression by eliminating the noisy activations altogether. Thus, max pooling is better than average pooling. Convolutional layer along with pooling layer forms the k^{th} layer of CNN. The number of these layers depends upon the complexity of the features to be extracted from the input image.

4. *Fully-connected layers*: These layers carry out the same operation as done by conventional ANNs in order to generate class scores from the activations; to be used for classification. In this layer, CNN performs classification of the learned features from previous layers. This layer flattens the compressed image generated by the last convolutional layer into a column vector that is fed into a feed-forward neural network in order to train the network with back propagation algorithm.

The CNN architectures applied in this research are

1. Alexnet
2. GoogleNet
3. ResNet-50
4. VGGNet16
5. VGGNet 19
6. Inception V3

2 Review of Literature:

With the increase in availability of massive medical data, the need of mining vital information out of these large voluminous data became very important. This encouraged the AI community to develop more efficient data mining tools and techniques. This scenario also prompted researchers to move ahead of conventional machine learning algorithms which were dependent on hand crafted features. Deep learning, which has its roots in neural networks emerged as an efficient and innovative tool for processing medical data. Deep Learning has the potential to reshape the future of medical diagnosis. Rapid development in computer processing power coupled with huge storage and parallel processors enabled the deep learning algorithms to make the most impossible the possible. Deep learning has been applied in diagnosis of wide range of medical problems. Most times, deep learning methods have outperformed those techniques which were based on visual descriptors for classification of cancers. A stacked autoencoder was designed by [1] for detection and classification of cancer form microarray gene expression dataset. [2] proposed a system for classification of various types of cancers. The system was based on deep belief network coupled with active learning to find the best features from genes in microRNA. Likewise, many researchers have applied deep learning techniques in molecular biology for prediction and classification of diseases. The rise of deep learning is also because of many open-source packages. But there is no clear formula or method to choose model architecture. As compared to conventional machine learning algorithms, the deep learning approaches scale much better with the large datasets but the computational cost is very high. In modern medicine, automatic medical image analysis is very important. Manual diagnosis by interpreting the medical images can be highly biased and time consuming. CNN a well-known algorithm in deep learning has performed outstandingly in computer vision and semantic analysis of medical images. CNN has shown promising results in automated understanding of medical images, medical image segmentation and shape analysis [3][4]. Greatest challenge in automated medical image analysis is variation in imaging protocols. In many cases, the intensity range of abnormal tissue may overlap with that of normal tissue. In order to alleviate these problems, deep learning provides the possibility to automate and merge the extraction of relevant features with the classification procedure [5][6]. CNN has been applied to many medical imaging problems like classification of lung disease by using CT images [7] diagnosis of TB from X-ray images [8], prediction of hemorrhages from color fundus images [9] etc. Before the advent of deep neural networks, the researchers have extensively applied conventional machine learning algorithms in cervical cancer classification. [10] proposed a model based on feed forward neural network trained by Levenberg Marquardt algorithm for the classification of cervical cell images into respective stage of diagnosis. [11] proposed a novel hybrid ensemble technique which was actually an ensemble of ensemble methods for staging of cervical cancer by classifying into respective classes. [12] Developed an artificial neural network-based classifier for the classification of cervical cell images to normal and abnormal classes. Oriented local histogram technique (OLHT) was applied for enhancing the edges of cervical cell images. After applying OLHT dual tree complex wavelet transform (DT_CWT) was applied to produce a multi resolution image. Features such as wavelet, grey level co-occurrence matrix (GLCM) and local binary pattern features were extracted from the transformed multi resolution image. These extracted features were then used to train and test a feed forward back propagation neural network.[13] In an automated cervical cancer diagnosis image classification is a vital step and many algorithms have been proposed for classification of cervical cancer images.

2. Methodology:

In conventional machine learning approach require hand crafted feature extraction to make a neural network learn the input space. These handcrafted features do not have the ability to represent the major information of the ground truth which ultimately fails the neural networks to optimize a generalized decision boundary. A deep neural network, on the other hand, extracts the relevant features itself through a hierarchical interaction of nodes/neurons. The lower layer nodes represent more simple features; but as the number of layers add up, these features become more abstract and informative. These deep features can then be used to train the classifier within the deep neural network architecture. Training a deep neural network requires more computational power and time as compared to shallow neural networks. In order to avoid computational time and power, many a times these deep neural networks are used only as deep feature extractor. These deep features are then used to train shallow neural network for final classification.

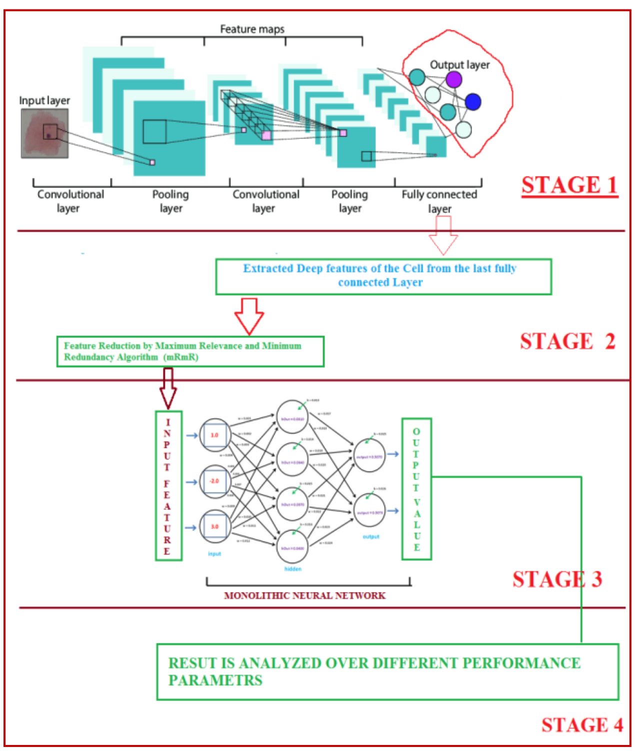

Fig. 4: Architecture using CNN as deep feature extractor and monolithic neural network as classifier

In this study, six well known convolutional neutral networks are used as feature extractor and three shallow neural networks are then trained on these deep features. These deep features are passed through mRmR algorithm for dimensionality reduction before forwarding to neural network. The architecture used in this experiment has four stages as shown in fig. 4. At stage 1, CNN are applied for deep feature extraction, these deep features are then reduced using mRmR technique in stage 2. At stage 3 a shallow monolithic neural network is trained over the reduced deep feature and finally results are analysed. The softmax layer of CNN is simply disposed-off

3. Results And Analysis:

The deep features extracted are reduced using mRmR technique; and out of total features, the best reduced feature set is searched along with the best monolithic neural network for classification. Three shallow neural networks are used as classifier along with each CNN. These shallow neural networks are Levenberg Marquardt neural network, One Step Secant and Scaled Conjugate gradient descent.

For seven-class classification of cervical cancer, the results are given in fig. 5 to fig. 10 and class wise performance metric values are tabulated in table 1 to table 6. These results shows that deep features extracted from Alexnet when reduced to 700 features, produced a classification accuracy of 81.66% when trained with LM neural network. In case of GoogleNet, the best classification result recorded is 81.80% and is produced by LM neural network when trained with 700 reduced deep features. Similarly, LM neural network produced best classification accuracy for both VGG 16 and VGG 19 when trained on reduced feature sets of 600. The classification accuracy is 81.65% and 80.92% for VGG 16 and VGG 19 respectively.

The best classification accuracy for seven class classification is produced by ResNet 50 along with LM neural network. The accuracy produced is 82.92% accuracy and it is the best classification accuracy for seven-class classification as compared to the other CNNs. Among all the classes of diagnosis, class 7 has the best F-value followed by class 1, whereas class 4 has the lowest F- value followed by class 5 and class 2. Lowest F-value indicates maximum misclassification. Inception V3 produced a classification accuracy of 81.65% by LM neural network trained on 400 features.

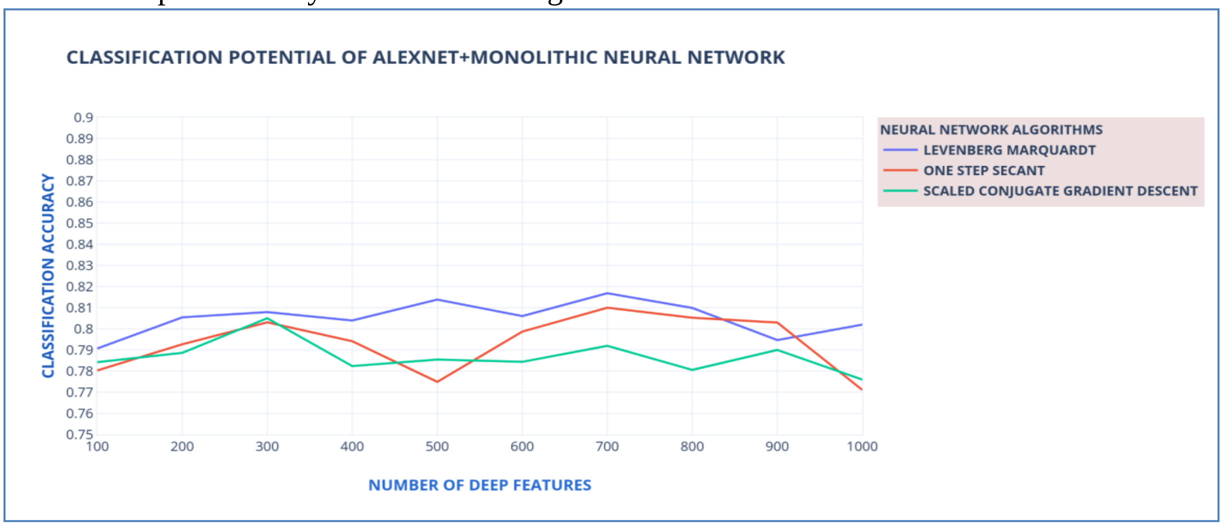

Fig.5. AlexNet with monolithic neural networks

Table 1: Class wise performance metric values AlexNet with LM neural network

Performance Parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Accuracy	0.816677						
Precision	0.83165	0.809836	0.735043	0.598039	0.759076	0.820652	0.932166
Recall	0.843003	0.762346	0.811321	0.824324	0.790378	0.838889	0.832031
F-Value	0.837288	0.785374	0.7713	0.693182	0.774411	0.82967	0.879257

Fig. 6: GoogleNet with Monolithic neural networks

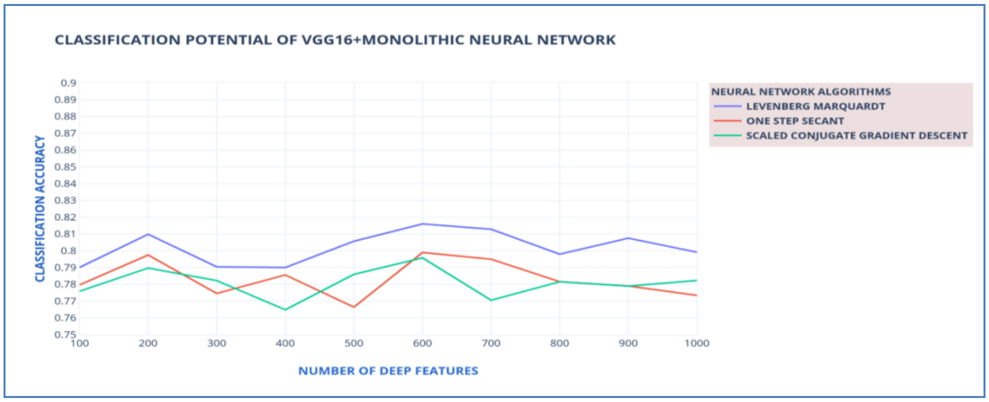

Table 2: Class wise performance metric values GoogleNet with LM neural network

Performance Parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Accuracy	0.81800						
Precision	0.866667	0.785714	0.729167	0.553571	0.78777	0.819178	0.933054
Recall	0.843003	0.746914	0.825472	0.837838	0.752577	0.830556	0.871094
F-Value	0.854671	0.765823	0.774336	0.666667	0.769772	0.824828	0.90101

Fig. 7: VGG16 with Monolithic neural networks

Table 3: Class wise performance metric values VGG16 with LM neural network

Performance Parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Accuracy	0.816554						
Precision	0.837838	0.811075	0.801843	0.792208	0.771626	0.75827	0.889117
Recall	0.846416	0.768519	0.820755	0.824324	0.766323	0.827778	0.845703
F-Value	0.842105	0.789223	0.811189	0.807947	0.768966	0.791501	0.866867

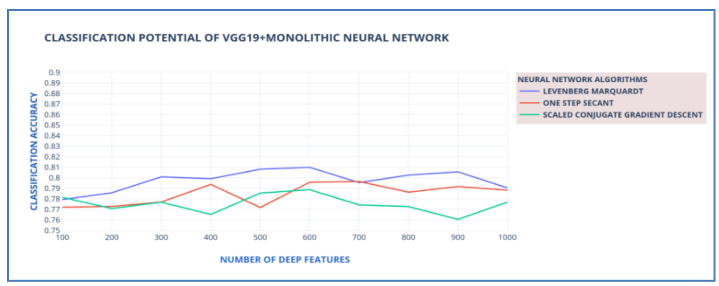

Fig. 8: VGG19 with Monolithic neural networks

Table 4. Class wise performance metric values VGG19 with LM neural network

Performance Parameter	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Accuracy	0.809293						
Precision	0.815436	0.813559	0.848039	0.712644	0.766551	0.742574	0.88391
Recall	0.829352	0.740741	0.816038	0.837838	0.756014	0.833333	0.847656
F-	0.8	0.7	0.8	0.7	0.7	0.7	0.8

Value	22335	75444	31731	70186	61246	8534	65404

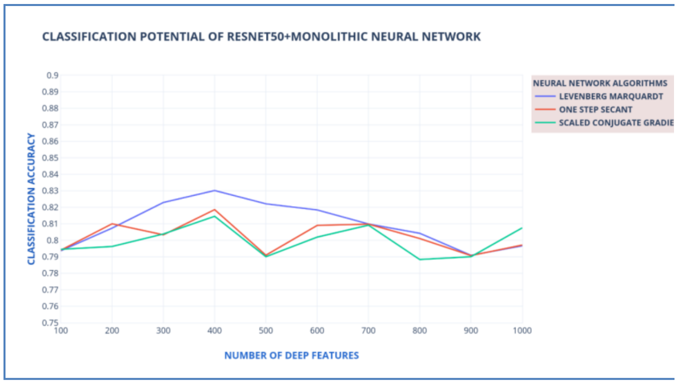

Fig. 9: ResNet50 with Monolithic neural networks

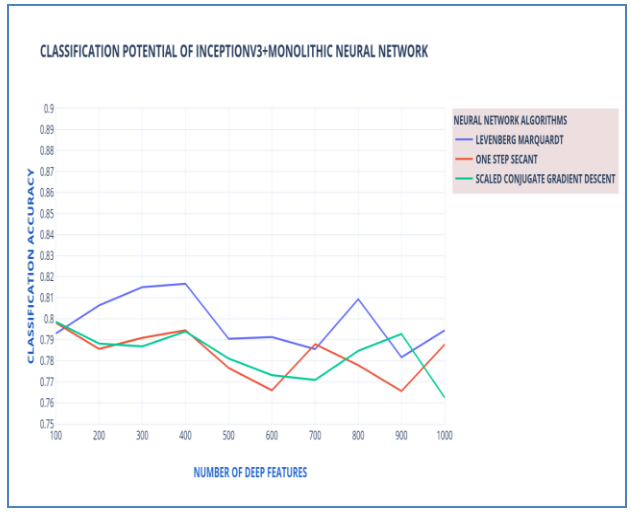

Fig. 10: InceptionV3 with Monolithic neural networks

Table 5 : Class wise performance metric values ResNet50 with LM neural network

Performance Parameter	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**
Accuracy	0.829622						
Precision	0.84106	0.847751	0.830189	0.717647	0.784983	0.754258	0.924051
Recall	0.866894	0.756173	0.830189	0.824324	0.790378	0.861111	0.855469
F-Value	0.853782	0.799347	0.830189	0.767296	0.787671	0.80415	0.888438

Table 6: Class wise performance metric values InceptionV3 with LM neural network

Performance Parameter	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**
Accuracy	0.816554						
Precision	0.819398	0.792994	0.8	0.570093	0.763699	0.821918	0.920668
Recall	0.836177	0.768519	0.792453	0.824324	0.766323	0.833333	0.861328
F-Value	0.827703	0.780564	0.796209	0.674033	0.765009	0.827586	0.89001

As two-class classification of cervical cancer is much easier classification problem as compared to seven-class classification and therefore the architecture produced much better result. The results of all the CNNs are given from fig. 11 to fig. 16; and class wise performance values are also tabulated in table 7 to table 12.

For two-class classification, the best classification accuracy is 94.77% achieved by ResNet50 with 400 deep features and LM neural network. The F-value of both the classes is above

92% for all the combination of CNN and shallow neural network.

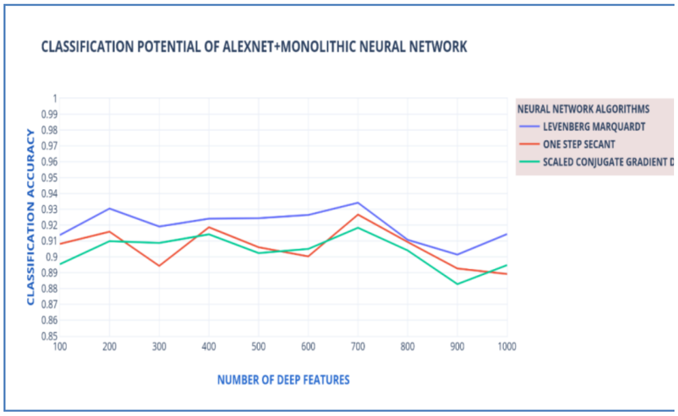

Fig. 11: AlexNet with Monolithic neural networks

Table 7 : Class wise performance metric values AlexNet with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.934172	
Precision	0.920966	0.944589
Recall	0.929125	0.938091
F Value	0.925028	0.941329

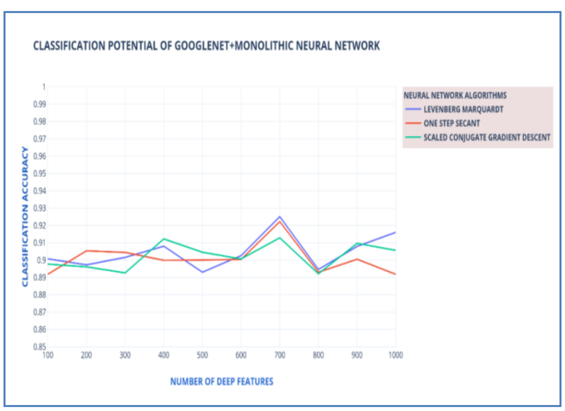

Fig. 12: GoogleNet with Monolithic neural networks

Table 8: Class wise performance metric values GoogleNet with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.92546	
Precision	0.917503	0.931565
Recall	0.911406	0.936371
F Value	0.914444	0.933962

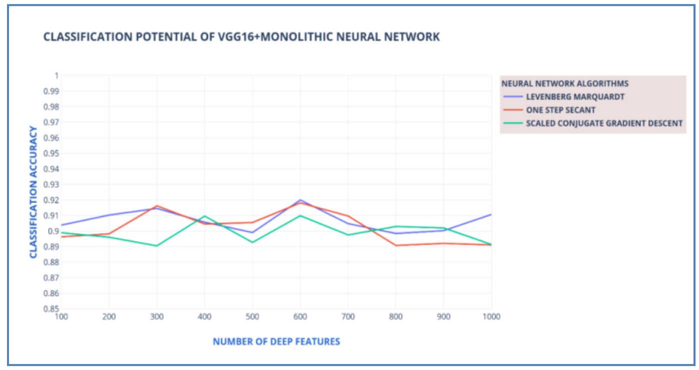

Fig. 13: VGG16 with Monolithic neural networks

Table 9: Class wise performance metric values VGG16 with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.919652	
Precision	0.908084	0.928633
Recall	0.908084	0.928633
F Value	0.908084	0.928633

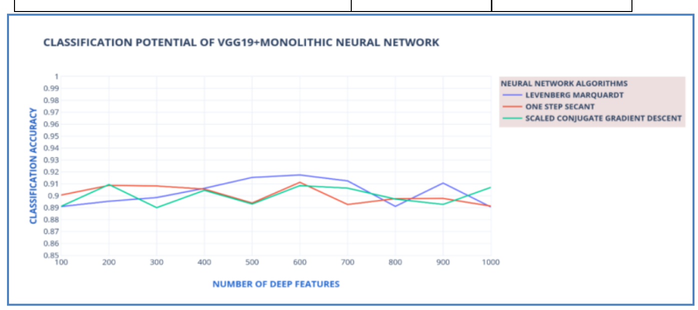

Fig. 14: VGG19 with Monolithic neural networks

Table 10: Class wise performance metric values VGG19 with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.917231	
Precision	0.896963	0.933566
Recall	0.915836	0.918315
F Value	0.906301	0.925878

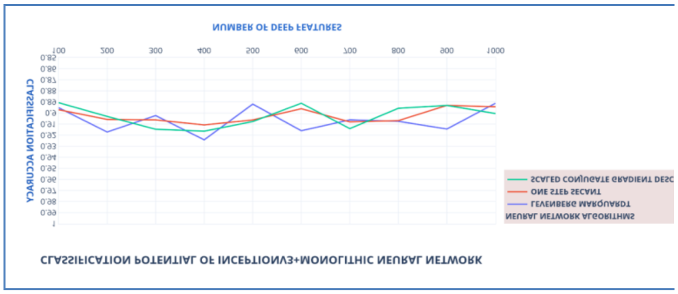

Fig.15. InceptionV3 with Monolithic neural networks

Table 11: Class wise performance metric values InceptionV3 with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.924008	
Precision	0.908991	0.935875
Recall	0.918051	0.928633
F Value	0.913499	0.93224

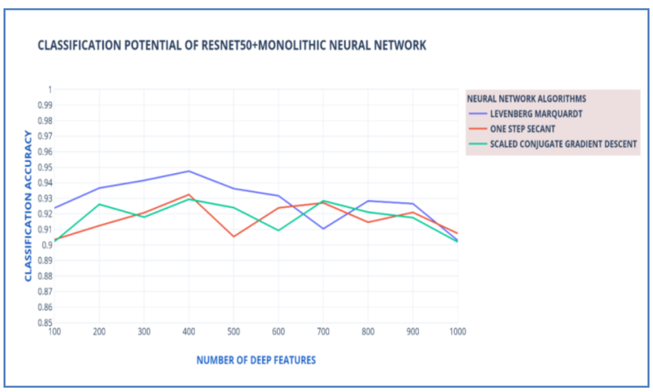

Fig. 16: ResNet50 with Monolithic neural networks

Table 12: Class wise performance metric values ResNet50 with LM neural network

Performance Parameter	Class 1	Class 2
Accuracy	0.947725	
Precision	0.941176	0.95279
Recall	0.939092	0.954428
F Value	0.940133	0.953608

4. Conclusion:

For simple and narrow medical disorders three approaches were used. The first approach is based on simple flowchart [14][15][16] i.e., a flowchart is used to design and develop an automated diagnostic system. Flowchart quickly becomes unmanageable when the problem size increases and is not able to include uncertainty which is a key element in most diagnostic problems. The second approach is based on probability theory [17][18][19] and the third approach is statistical pattern matching [20]. Both statistical and probabilistic approaches assume unnecessary assumptions such as that the diseases under serious deliberation are independent of each other and these diseases are exhaustive. Such problems could be avoided by creating a huge database of all probabilities but creating such a huge database is almost impossible in real world situation. In addition, all the diagnostic systems based on probability and statistical pattern matching is not able to explain the causality of disease and thus cannot explain the clinician the reason to reach the diagnostic conclusion.

In this experiment the classification potential of six (6) well known convolutional neural networks are assessed over the primary dataset of cervical cancer as feature extractor and 3 monolithic neural networks as final classifiers. The classification is done both at two class and detailed seven class classification. The greatest hindrance in machine learning algorithms is need for hand crafted feature extraction, and these features many times fails to represent the actual ground truth. The deep neural network on other hand extracts the relevant feature itself and uses those high dimensional data for training of the last connected layer. We have also compared the result of our study with the already published studies forclassification of cervical cancer cases using conventional machine learning algorithms. [11] proposed an ensemble of 15machine learningalgorithms, for 7 class classification of cervical cancer. The ensemble achieved an accuracy of only 78%. [21] Trained a model based on support vector machine and herlev dataset for seven class classification of cancer instances. Their systemexhibited an accuracy of about 81.85% and precision of0.84622, whereas our proposed system produced an accuracy of 82.92%.Neural Pap developed based on radial basis function produced a classification accuracy of 73.40% [22]. This accuracy is far lower than our reported accuracy

The results indicates that this study has notable accuracy and effectiveness to other studies.

References:

[1] R. Fakoor, F. Ladhak, A. Nazi, and M. Huber, "Using deep learning to enhance cancer diagnosis and classification," in Proc. Int. Conf. Mach. Learn., 2013, pp. 1–7.

[2] R. Ibrahim, N. A. Yousri, M. A. Ismail, and N. M. El-Makky, "Multi-level gene/mirna feature selection using deep belief nets and active learning," in Proc. Eng. Med. Biol. Soc., 2014, pp. 3957–3960.

[3] M. Havaei, N. Guizard, H. Larochelle, and P. Jodoin, "Deep learning trends for focal brain pathology segmentation in MRI," CoRR, vol. abs/1607.05258, 2016. [Online]. Available: http://arxiv.org/ abs/1607.05258

[4] H. Greenspan, B. van Ginneken, and R. M. Summers, "Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique," IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1153–1159, May 2016

[5] D. Nie, H. Zhang, E. Adeli, L. Liu, and D. Shen, "3d deep learning for multi-modal imaging-guided survival time prediction of brain tumor patients," in Proc. MICCAI, 2016, pp. 212–220. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-46723-8_25

[6] T. Xu, H. Zhang, X. Huang, S. Zhang, and D. N. Metaxas, "Multimodal deep learning for cervical dysplasia diagnosis," in Proc. MICCAI, 2016, pp. 115–123. [Online]. Available: http://dx.doi.org/10.1007/978-3-319- 46723-8_14

[7] M. Anthimopoulos, S. Christodoulidis, L. Ebner, A. Christe, and S. Mougiakakou, "Lung pattern classification for interstitial lung diseases using a deep convolutional neural network," IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1207–1216, May 2016.

[8] Y. Cao et al., "Improving tuberculosis diagnostics using deep learning and mobile health technologies among resource-poor and marginalized communities," in IEEE Connected Health, Appl., Syst. Eng. Technol., 2016, pp. 274–281.

[9] M. J. van Grinsven, B. van Ginneken, C. B. Hoyng, T. Theelen, and C. I. Sanchez, "Fast convolutional neural network training using selec- ´ tive data sampling: Application to hemorrhage detection in color fundus images," IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1273–1284, May 2016

[10] Sokouti, Babak, SiamakHaghipour, and Ali Dastranj Tabrizi. "A framework for diagnosing cervical cancer disease based on feedforward MLP neural network and ThinPrep histopathological cell image features." Neural Computing and Applications 24.1 (2014): 221-232.

[11] Sarwar, Abid, Vinod Sharma, and Rajeev Gupta. "Hybrid ensemble learning technique for screening of cervical cancer using Papanicolaou smear image analysis." Personalized Medicine Universe 4 (2015): 54-62.

[12] Elayaraja,Suganthi, "Automatic Approach for Cervical Cancer Detection and Segmentation Using Neural Network Classifier" , Asian Pac J Cancer Prev. 2018; 19(12): 3571–3580.

[13] Kudva, V., Prasad, K. and Guruvare, S., "Automation of detection of cervical cancer using convolutional neural networks", Critical Reviews™ in Biomedical Engineering, 46(2).2018.

[14] Schwartz, William B. "Medicine and the computer: the promise and problems of change." Use and Impact of Computers in Clinical Medicine. Springer New York, 1970. 321-335.

[15] Lusted LB. Introduction to Medical

Decision Making. Springfield, Illinois: Thomas;1968.
[16] Bleich, Howard L. "Computer-based consultation: Electrolyte and acid-base disorders." The American journal of medicine 53.3 (1972): 285-291.
[17] Gorry, G. Anthony. "Computer-assisted clinical decision making." Methods of Information in Medicine 12.1 (1973): 45
[18] Kassirer,J.P.,&Gorry,G.A.(1978).Clinicalproblemsolving:abehavioralanalysis. In *Computer-assisted medicaldecisionmaking*(pp. 85-107). SpringerNew York.
[19] De Dombal, F. T., Leaper, D. J., Staniland, J. R., McCann, A. P., &Horrocks, J. C.,Computer-aided diagnosis of acute abdominal pain. Br Med J, 2(5804), (1972),9-13.
[20] Rosati, R. A., McNeer, J. F., Starmer, C. F., Mittler, B. S., Morris, J. J., & Wallace, A. G., " A new information system for medical practice", Archives of Internal Medicine, 135(8), 1017-1024, 1975
[21] Mariarputham EJ, Stephen A (2015) Nominated texture based cervical cancer classification. In: Computational and mathematical methods in medicine, Hindawi Publishing Corporation, vol2015, Article ID 586928, p 10
[22] . Sulaiman SN, Mat-Isa NA, Othman NH, Ahmad F (2015) Improvement of features extraction process and classification of cervical cancer for the NeuralPap system. In: 19th International conference on knowledge based and intelligent information and engineering systems, Procedia Computer Science, Elsevier vol 60, pp 750–759