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Classification of Cervical Cancer using Artificial Neural Networks

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Abstract

Artificial neural network (ANN) plays an important role in many medical imaging applications. The detection of cervical cancer cells uses an ANN for classifying the normal and abnormal cells in the cervix region of the uterus. Cervical cancer detection is very challenging because this cancer occurs without any symptoms. The classification between the normal, abnormal and cancerous cells is identified by using an artificial neural network which produces accurate results than the manual screening methods like Pap smear and Liquid cytology based (LCB) test. The ANN uses several architectures for easy and accurate detection of cervical cells. In this paper, a survey and analysis on the different types of architecture in the ANN with its accuracy results and performance are discussed. A brief description about the working and detection of cervical cancer is presented which is useful for the classification of normal and abnormal cervical cells.

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Keywords: Artificial Neural Network (ANN); Cervical Cancer; Liquid Cytology Based Test (LCB); Pap Smear Test.

1. Introduction

Cervical cancer is the second and common cancer that occurs in women of all age groups. This cancer is a deadly disease because it cannot be screened with any symptoms at the initial stage. The Pap smear test is a manual screening method used for collecting the cervical cells from the cervix region of the uterus. The doctor or the physician collects the cervical cells manual with a brush or spatula. The collected cervical cells are sealed in a container which is sent to the laboratory for manual classification of the normal and abnormal cervical cells. There are only few experienced pathologist to carry out this screening process. However, this method suffers from high false positive rates due to human errors in the classification of cells. This method is very cost effective and a pathologist can classify only 4 to 5 slides per day. The process is difficult to be performed at a faster rate because of the irregular boundaries of the cytoplasm and nucleus present in cell structure. The nucleus may be overlapped with other cells and it is difficult for the boundaries to be detected for a single cell and performing the classification is tedious. The second most common screening method is the liquid cytology based (LCB) method which immerse the collected cervical cell samples in the liquid of 5% acetic acid. The cervical cells are classified under three types of tissues Squanomus epithelium (SE), columnar epithelium (CE) and Aceto white region (AW). The AW tissue changes its colour into white region when immersed in acetic acid for abnormal classification of cells. This method suffers from accurate results of classification.

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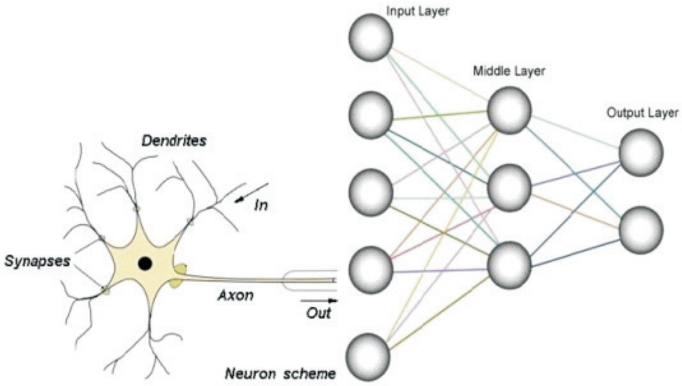

Fig. 1. Architecture of ANN.

To enhance the manual screening method and produce accurate results in the detection of cervical cancer the artificial neural networks are used to produce accurate results and perform in an easy manner. There are three layers used in the architecture of ANN which consists of the input layer, hidden layer and output layer. The number of each layer depends on the input images fed which connects to each layer with the neurons. The Fig. 1 illustrates the three layers connectivity with neuron structure where nodes are used for each layer.

The total number of nodes or layers in each ANN is dependent on the number of input images used. The input layer process and connects itself to the hidden layers depending on the data set used by the input layer. There are two types of data set trained and untrained data set which produces the accuracy by using a supervised and unsupervised learning approach with different type of neural network architectures like feed forward, back propagation method which uses the data set at a different manner. The rest of the paper is organised as follows: Section 2 gives a detailed description about the different types of neural networks with the respective architecture, Section 3 summarises the different types of neural networks with a complete survey table with a discussion of the networks and finally the paper is concluded in Section 4.

2. Artificial Neural Networks (ANN)

Royan Dawud Aldian *et al.*[1] propose an automatic classification for normal and abnormal cervical cells with artificial neural networks (ANN) and learning vector quantification (LVQ). The sample data sets are collected which performs the steps in digital image processing like pre-processing, filtering and feature extraction. The input image is stored in ANN and for the classification of cervical cells for detection of cancer the LVQ method is used for calculating the coefficient mean value of the extracted image which is used for classifying the normal and abnormal cell with 90% accuracy result. Fatemeh Hoda Moghimi *et al.*[2] propose artificial neural network (ANN) techniques used for the health clinic purpose where a multi-layered perceptron is used in the ANN to map the thinking and key components. The architecture of ANN consists of one input layer and one output layer with no restriction in the number of hidden layers used. The ANN is used in all medical applications and can be easily mapped with the learning approaches for better understanding and results. Aabha S. Phatak *et al.*[3] propose a new method for detecting cervical cancer with Support vector machine (SVM) and Artificial neural network (ANN) for detection of cervical uterus cancer. Soorya Praba *et al.*[4] provides a comparison in the Pap smear classification methods with neural networks; k nearest neighbour and Bayes classifier. The three classifiers are used for the classification of normal and abnormal cells. The input image is fed where the features required are extracted for the classification results. A three layered ANN is used which is used with the input, output and hidden layer. The data set used is a trained data set which produces accurate results than other classifiers. N. Mustafa *et al.*[5] propose a methodology with artificial neural network by extracting the new features of cervical cells. The input image is obtained from the Pap smear slides where the perimeter, area, red, blue and green colour are extracted with their intensity levels which helps the ANN to classify the cervical cells into normal and cancerous cells.

2.1 Multi-Layer Perceptron (MLP)

Babak Sokouti *et al.*[6] proposed a novel Pap smear test performed for cervical cancer, which is not efficient because of the overlapping cells and inexperience pathologist. To diagnose the cervical cancer cells a multi-layer (MLP) neural network is used which has two phases, namely, image pre-processing and feed forward MPL neural networks. The Levenberg-Marquarat feed forward MLP neural network classifies the unsegmented cell features as normal, LSIl, HSIL cells. This network is capable of estimating the non-linear functions with high accuracy. J. Ramirez *et al.*[7] demonstrates the histological images characterisation taken from microscope, which does not have significant parameters. the infrared (IR) is widely used in the treatment of cancer for detecting the normal and abnormal cells. The new add on features of IR is fed into a multi layered (MLP) network where the cervical features are extracted by thin Prep[8]. Isabelle Claude *et al.*[9] presented a novel method for the contour detection around the cervical cells classified with artificial neural network which is used to quantify the contours and blurred within the spatial parameters. Ganesan *et al.*[10] propose a new method in detecting cancer with artificial neural network by using dimorphic data. The intelligent information is retrieved from the network. The data set used is an untrained data where a back propagation method is used for detecting the weights used in the neural network design. The MLP architecture is used with the input layer, hidden layer and the final output layer. Paulo J. Lisboa *et al.*[11] propose an Artificial Neural Network method for detecting the cancer cells with decision support systems used in clinical trials under a comparative study analysis. There are many techniques embedded with the ANN to detect the cancer cells in patients. Many such techniques are embedded in clinical trials for detecting cancer in patients. The MLP network and the PAPNET networks are analysed with respect to each other in their performance with clinical trials. P. J. G. Lisoba[12] presents a review of evidences in health benefits by using artificial neural networks with MLP architecture. There are many benefits of health care systems using ANN. The nodes are connected in the layer where the input image is given as an MRI image for clinical usage. The MLP architecture gives better accurate results and supports the decision.

2.1.1 Cascaded multi-layered preceptor

Intan Aisdha Yusoff *et al.*[13] the pathologist for diagnosing cervical cancer are in short numbers which is a major drawback in cervical cancer. The input to the neural network is given as the cell features. The performance of two neural networks architectures is analysed in the proposed system. The cascaded multi-layered preceptor (C-MLP) and extreme learning machine (ELM). The trained data set was tested as inputs and it gives accuracy. In C-MLP network there were eight inputs and three outputs which diagnosis are normal, LSIL or HSIL cells.

2.1.2 Hybrid multi-layered perceptor

Zati Athiar Ramli *et al.*[14] proposed a new method to classify the cervical cells into normal and abnormal cells. A hybrid multi-layered perception with least square algorithm is used. The hybrid multi-layered preceptor (HMLP) network has one hidden layer where each layer has its own nodes in a form of non-linear model. The input layer acts as a data holder which distributes the input to the hidden layer and output layer. The output from the hidden layer becomes the input to the output layer. The HMLP network is superior to MLP and gives better specificity results. The classification of cervical cells is made as normal, low-grade squamous epithelium cells. The construction of HLMLP network is focussed to give lower sensitivity results and reduce the false positive rate in cervical cancer diagnosis. In the manual screening Pap smear test, certain features are extracted at the pre-processing stage which is termed as the Bethesda system (TBS). The rules in TBS are translated into fuzzy rules to detect the Pap smear slides into normal and abnormal cells. The classification abnormalities of epithelial cells are of two types ASCUS and a typical glandular cells of undetermined significance.

2.2 Back propagation neural network

The liquid based cytology (LCT) is a manual screening method which is used for screening cervical cancer. It is a faster and also high quality. The classification of the segmenting the cervical cell nuclei using BP neural network where 15 alternative feature parameters is used. The principal component Analysis (PCA) method is used for extracting the optimised feature parameters within the nucleus. The BP neural network removes the high statistical correlation between feature extractions. A three layered feed forward neural network is used for classifying the segmented single nuclei[16]. Mehdi Bazoon *et al.*[17] propose an artificial neural network (ANN) with back propagation (BP) method. The cervical cells slides are classified as mild, moderate and severe cells. The ANN uses three layer approaches where the training set with adaptive resonance theory (ART) is used with ANN as a supervised classifier. The nucleus is observed with certain abnormalities for its classification with ART for screening the abnormal nucleus.

2.3 Gene expression

Gene programming is a similar approaches same as genetic algorithm. The gene expression programming is proposed to compare with three types of neural networks like multilayer preceptor (MLP), a radial basis function neural network and probabilistic neural network. In GEP the chromosomes as linear strings of fixed length. The structure of gene is organised as head and tail. The length of gene depends on head size. In MLP networks the input is fed through number of layers. The input layer is the features of the input pattern, hidden layer is the predefined number of nodes called neurons and the output layer is composed of neurons that determine the final response of the model[18].

2.4 Radial basis function network

In radial basis function neural network, the input is composed of the neurons for each predictor variable. The probabilistic neural network uses a Bayes classifier with four layers for which each neuron is associated with data attribute. Kagan Tumer *et al.*[19] propose a radial basis function (RBF) networks with ensemble algorithms for the detection of cervical pre cancer. The RBF networks are feed forward neural networks with a single hidden layer. One class of the RBF consists the Gaussian kernels for activation function. The experiment was conducted for both the RBF and MLP neural network. The MLP network has three units with a single hidden layer. The RBF network uses the k means algorithm to train the dataset. Francisco J. Gallegos-Funes *et al.*[20] propose a radial basis function (RBF) with rank M-type for classifying the Pap smear slides for detecting cervical cancer by extracting the features of nucleus and cytoplasm.

2.4.1 Fuzzy RBF network

Kwang Balk Kim *et al.*[21] demonstrate a new nucleus segmentation and recognition method where the cell region is extracted from the uterine cervical region. The extracted image is portioned into RGB space value. A k-means clustering algorithm is used to classify the RGB space as R, G, and B channels. This is the input information which is transformed into HSI model to be used in fuzzy RBF network. The fuzzy c-means algorithm is used in the neural network to generate the middle layer. The HSI model acts as the input layer. The output layer is connected from the middle layer which is classified into NNL, ASCUS, LSIL, HSIL and SCC where WNL normal and other cells are abnormal cells. SCC is the cancer cell.

2.5 Convolution neural network (CNN)

The accurate segmentation of cervical cytoplasm and nuclei is very challenging task in cervical cells. A super pixel which uses a convolution neural network (CNN) based segmentation is proposed for more accurate results. The segmentation of cytoplasm is performed first. The CNN shares the similar network features to biological networks. The patterns which are known can be trained by using this network by mapping the numerous input and output. Thus in this way the complexity of the network model is reduced by eliminating the weights in the networks. The cells and background colours are distinguished with the features to be fed as the input to the network[22].

2.6 Multi fractural analysis

Bondarenko *et al.*[23] presented a multifractal analysis combined with self-organization maps approach for the discrimination of normal cells from malignant. The Pap smear slides are given as the input with the analysis of the images provided a data set of cell features. The neural network is used as a classifier to classify the normal and malignant cells based on the extracted features of multi fractural. The self-organization map is used for accurate classification of both cells and patient level. It is used as a neural algorithm which is based on unsupervised learning. The input layer is the feature vectors which measures the neurons for each dimension, the output layer is organised as two dimensional arrays of neurons. Zhong Li *et al.*[24] demonstrates that in the pre-processing stage, the features are extracted from the given input Pap smear slides. The Bethesda system (TBS) rules are translated into fuzzy rules which classifies the pap smears into normal and abnormal cells. The feed forward neural network with fuzzy for classification is unclear.

2.7 Feed forward neural network

Bondarenlo *et al.*[25] propose a new method for selecting the features from the biomedical images of cervical cancer. There are three approaches used like the wavelet analysis, the brute force approach and the last is the combination of the two approaches. After the feature vectors are extracted from the image, it is classified by using neural networks. The statistical wavelet analysis is used to measure the fluctuations in the noise level and it is less sensitive. The feed forward neural network with a single hidden layer is used with the back propagation method where the input is given as n units with an n dimensional input vector. Takashi Ochi *et al.*[26] demonstrate a new method using the artificial neural network (ANN) for predicting the survival of cervical cancer patients. The histology radiations are combined with ANN for the prediction levels in the patients by the examination of biopsy tissues. A feed forward ANN with back propagation learning model is implemented with input, hidden and output layer. Jennifer Hallinan[27] proposes a new approach using artificial neural network (ANN) for detecting the malignancy in cancer. The ANN classifier uses a three layer feed forward neural network with sigmoid function is used to encode each net as an eight bit binary value. The ANN uses genetic algorithm (GA) to reduce the mean squared error of the training set data in the network. The fitness value is selected for maximum parameter to be choosing based on mean square error. The receiver operating characteristic curve (ROC) is used to measure the ratio of false positive and false negative values. Nikolaos Ampazis *et al.*[28] propose a new second order neural network classifier for Pap smear classification of cervical cells. The two training algorithms used are the LMAM (Levenberg-Marquardt with Adaptive Momentum) and OLMAM (Optimized Levenberg-Marquardt with Adaptive Momentum). The LM method is used for testing the non-linear squares. A feed forward neural network is used where the squanomus epithelium is divided into four regions basal, parabasal, intermediate and superficial layer.

2.8 Knowledge based networks

Pabitra Mitra *et al.*[29] propose a system with hybrid approach for detecting cervical cancer. The knowledge based neural networks is used for the extracting the image with respect to knowledge based rule. The genetic algorithm calculates the pixel value of the image for detecting cervical cancer. The algorithm uses MLP layered architecture for extracting the rules in the network.

2.9 Modular neural network

Pabitra Mitra *et al.*[30] propose a new artificial network with rough set theory and ID3 algorithm. A hybrid approach is used with a MLP network where knowledge based subnetworks are used for detecting the cervical cells connected to the network. The modular neural network (MNN) is a form of ANN which is used for larger storage and extracting the logic rules of the system.

3. Discussion

The detection of cervical cancer is very challenging task in the medical analysis because of the tedious effort in segmenting the cervical cells and later classify them into normal, abnormal and cancerous cells. The manual classification of cervical cancer suffers from many drawbacks which lead to the discovery of automated or computerised classification methods. The cell structure of the cervical cell is complex with its structure where the

Table 1. The Analysis on Cervical Detection using Artificial Neural Networks.

Author's Name	Merits	Demerits	Dataset	Accuracy
Royan Dawud Aldian *et al.*[1]	Performs better classification	Time consumption is not discussed	80 single cervical image	90%
Fatemeh Hoda Moghimi *et al.*[2]	Capability of ANN is increased	Prototype must be developed	–	–
Aabha S. Phatak *et al.*[3]	Features are extracted clearly	Segmentation is not efficient	40 MRI images	–
Soorya Praba *et al.*[4]	Noise is removed clearly	Feature extraction must be enhanced	–	
N. Mustafa *et al.*[5]	New features are extracted	Diagnostic performance must be increased	508 data Hospital University Sains	94.29%
Babak Sokouti *et al.*[6]	Precancerous cells are detected easily	Overlapped cells are not clear	1,100 cells Aizahra Hospital	90%
J. Ramirez *et al.*[7]	Labelling pixels with value is easy	Efficient algorithm can be used	RGB color histogram	–
Jusman *et al.*[8]	Abnormalities are detected easily	Nucleus and cytoplasm boundaries can be enhanced	176 cervical scraping	98.2%
Isabelle Claude *et al.*[9]	Threshold value is used for calculations	Color parameters are not discussed	30 Lugol images	95.8%
Ganesan *et al.*[10]	Selection of weights is increased	Performance measurement is not discussed	–	–
Paulo J. Lisboa *et al.*[11]	Decision support system is used for the study of techniques	Classification of cells is missing	–	–
P. J. G. Lisoba[12]	Performance comparison is analysed	Image analysis can be made clearly	–	–
Intan Aisdha Yusoff *et al.*[13]	Interpretation of data is easy	Cell structure must be detected	–	96.02%
Zati Athiar Ramli *et al.*[14]	Cost effective diagnosis	Larger data set is inefficient	–	82.63% accuracy, 73% sensitivity and 93.33% specificity
Gonez Mayorga *et al.*[15]	Estimator calculates the ratio easily	Irregular boundaries are not detected	78 cervical cell images	83% sensitivity 100% specificity
Wang Xiaoning *et al.*[16]	Easy classification of cervical cells	Dependent on certain parameters	407 cervical images	–
Mehdi Bazoon *et al.*[17]	Features are extracted easily	Abnormalities are not clear	800 input nodes	0 false negatives and 2.8% false positives
Maciej Kusy *et al.*[18]	Increased reliability	Evaluating factor is not clear	–	76.02%
Kagan Tumer *et al.*[19]	Kernels are used for easy activation	Class of output layer is not presented	–	–
Francisco J. Gallegos *et al.*[20]	Parameters are estimated clearly	Comparative results can be enhanced	Pathologic Anatomy images	–

Table 1. (Continued).

Author's Name	Merits	Demerits	Dataset	Accuracy
Kwang Balk Kim *et al.*[21]	Effective segmentation	More morphometric features can be extracted	20 samples of cevicalcells	80%
Youyi Song *et al.*[22]	Segmentation efficiency is high	Classification can be more clear	1400 samples cells	–
Bondarenko *et al.*[23]	Texture identification is easy	More clear image analysis can be done	102 sample cells	–
Zhong Li *et al.*[24]	New features are extracted	No morphological operations	80 sample cells	80-98%
Bondarenlo *et al.*[25]	Noise removal detection is clear	Efficient architecture must be replaced	50 sample cells	–
Ochi *et al.*[26]	Increases ANN efficiency	Time consumption more	–	–
Jennifer Hallinan[27]	Reduces more falser rates	Efficiency is less	–	–
Nikolaos Ampazis *et al.*[28]	Easy detection	More operations can be reduced	–	–
Pabitra Mitra *et al.*[29]	Integrated methods increase the efficiency	More layers confusion	–	–
Pabitra Mitra *et al.*[30]	Genetic operators are eased for easy operation	Effective data analysis and algorithm can be used	–	–

nucleus and cytoplasm cannot be detected easily due to the presence of irregular boundaries, overlapping cell regions. The Artificial Neural networks are widely used in many medical applications with accuracy in performance results. The network uses many different architectures and methods which detects the cervical cancer at the earliest stage and increases the mortality rate of women patients. The ANN[1,2] is used with respect to three layers which are connected by the nodes and obtain the transition from the neurons in the brain cells. The multi layered perceptron is used as an ANN architecture which performs the detection at a faster rate[6,7]. The input is obtained from the input layer and the processing functions or data is stored in the hidden layer which is connected to the output layer where the results are obtained. The radial basis function is used in the ANN to restrict or process the input value with[19] a computing function for obtaining accurate results. A CNN neural network is used[10] with a convolution factor which can be made dependent or independent depending on the input image value. Many medical applications are carried out with the feed forward neural network which is used for the easy and fast detection of the input value[25] with many different techniques are embeded and compared. The network forms a link within the node structures and a performance measurement is used for the evaluation of performance of the networks. The knowledge based neural network is used for extracting the rules fed to the ANN easily[29] where the input image is mapped with the rules fed into the network and extracts the features accordingly in the order. The classification of the cells is dependent with the size and features of the nucleus and cytoplasm extracted. The nucleus and cytoplasm ratio (NCR) performs a major role in detecting the cancerous cervical cancer cells. The ANN classification method produces better classification results with good accuracy rate which helps the health care or clinical trials to detect the cervical cancer at the earliest stage in women's. The algorithm used in each ANN architecture can be enhanced more in future for better and promising results in the detection of cervical cancer. The learn thinking capability will be embedded in ANN in future process which helps to increase its efficiency in a dynamic platform with good performance evaluation.

4. Conclusions

The Artificial neural network plays an important role in many medical image analysis applications due its accuracy in experimental results. The neural network architecture uses many algorithms which increases the efficiency of the accuracy in results. The classifications of the normal and abnormal cervical cells are connected to the network which helps to detect the cervical cancer at the earliest stage. In this paper, the different types method used for the detection of cervical cancer based on neural networks and its architecture are discussed. In future, a Gene feedforward neural network with a combination genetic algorithm with feedforward neural network will be proposed for detecting cervical cancer.

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