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Learning Techniquesforpre-Malignancy Detection in Human Cells a Review

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Abstract: ***Cancer is uncontrolled cell growth which starts consuming cell nourishment and keeps on multiplying indefinably. There are 100 plus different types of cancers that may affect any part of the body. In the past 26 years, the cancer incidence rate has been changed drastically in India. To control it early-stage detection of cancer plays a very important role. Early-stage detection of cancer helps in better diagnosis will also lower the chances of dying due to this deadly disease. It will impact considerably on the patient's recovery when it is more treatable. Early Cancer detection or premalignant disease detection in the human body is possible through screening tests. Several screening methods have been tested, applied and proven to be very much efficient in reducing death rate due to cancer. This paper survey's how learning techniques can be efficiently applied, tested and showed promising results in early-stage cancer detection through several screening methods***

Keywords: Cancer, Early Detection, Machine Learning, Screening Methods, Statistics

I. INTRODUCTION

Cancer is a disease of major concern in India in the past couple of years. Due to environmental factors, lifestyle, stress and drastic changes in our day to day activity number of cancer patients is increasing [1]. It is becoming a common disease with an increasing mortality rate, as per NICPR data 0.3 million deaths per year, it almost got double in the last 26 years and numbers are still not reducing till date 12. There are different types of cancer that may affect any part of the body based on multiple factors. The most common type ofcancers is cervical, lung, breast, colorectal, liver. The risk of developing cancer before the age of 75 in men is 9.30% and women 9.40%. Only in 2018 around 4 lakh male patients and around 3 lakh female patients died because of different cancers. The current statistics are based on ICMR and NICPR data3. The government has laid down four priority cancers which are breast cancer, cervical cancer, oral cancer, and lung cancer which together constitute 41 percent of cancer burden, the report mentioned by NICPR.

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Oral Cancer is among the top three cancers in India, number one among all cancers in men, and number three among female cancers. Breast cancer is first in females and then cervical [10,11,12].

II. LITERATURE REVIEW

India is a geographically diverse country where each state shows a significant increase in the specific types of cancer patients. The common risk factors which are observed mostly are pollution, consumption tobacco, and alcohol, use of pesticides, Dietary habits, etc. The following summary shows cancer incidence rate, leading cancers and risk factors state-wise 5. In Last 26 year there are drastic trend changes in cancer incidence rate. In 1990 only 3 states were reported with high cancer incidence rate while 11 states reported moderate rate further 10 states were reported less incidence rate and only one state very few cases of cancer incidence cases7. Today after 20 years there 7 states with very high incidence rate while 19 states are reported high to moderate rate and only one state have low incidence rate7.Given statistics are shown in details in Table 1

III. MOTIVATION

Statistics mentioned in given table are fearsome so, to reduce it, researchers, doctors and scientists are working together to develop new techniques, new medicines to cure cancer. From the past few years, Computer-aided methods are being used to analyze the clinically obtained data. Data is processed and generates some result which can be used to get information about cancer38. One of the noble causes of machine learning will be detecting cancer in its early stages by analyzing input obtained from various screening methods. Screening is looking for malignancy before it shows any symptoms. Machine learning along with data obtained through screening methods will boost the result with great accuracy as compared to the traditional approach. To get the cancer incidence rate, the age-adjusted rate is between 45-70 is considered in which most of the cancer patients were diagnosed 37.

Region	Cancer Incidence rate Per 100000	Leading cancer	Risk factors
Arunachal Pradesh	Very High >105	Oral , Stomach, Lung, Breast	Tobacco, household burning of firewood, Lack of proper awareness
Assam	High 90-105		
Mizoram	Very High >105		
Nagaland	Less 60-75		
Manipur	Less 60-75		
Meghalaya	Moderate 75-90		
Tripura	Moderate 75-90		
West Bengal	Moderate 75-90	Lung , Urinary Bladder	Air and Water Pollution, Personal Hygiene
Odessa	Moderate 75-90	Cervical	
Jharkhand	Less 60-75	Mouth, Lung cancer, Cervical , Breast	Tobacco, Pollution, coal dust, Industrial smoke
UP , Bihar	Moderate 75-90	Gall bladder , Lung , cervical	Polluted water, Diet rich in animal protein , Sediments in water
Madhya Pradesh	Moderate 75-90	Oral	Tobacco , Pan masala
Chhattisgarh	Moderate 75-90	Throat , Skin	Unusual sexual activities,
Telangana	Less 60-75	Lungs , Stomach , Cervical	Obesity , pollution, Alcohol consumption
Andhra Pradesh	Moderate 75-90	Lungs , Stomach , Cervical	
Tamilnadu	Moderate 75-90	Stomach , Cervical , Oral	Tobacco, Obesity, eating habits
Karnataka	Moderate 75-90	Stomach cancer	Spicy food diet
Kerala	Very High >105	Lung, Liver, kidney	Diabetes, Pollution residues ,Unhealthy eating habits
Goa	High 90-105	Colon cancer , Breast , Cervical , Oral	Red meat , Alcohol , Tobacco
Maharashtra	Moderate 75-90	Breast , Lung , Oral	Stress full life style, Pollution, Tobacco and alcohol consumption
Gujarat	Moderate 75-90	Head and neck , Oral	Tobacco , Gutkha , Pan masala
Rajasthan	Less 74-62	Breast , Cervical , Ovary Lungs , Prostate , Oral	Tobacco, polluted food items, Personal hygiene
Haryana	High 90-105	Oropharynx, Cervical, Lung	improper sanitation, excessive use of fertilizers,
Punjab	High to moderate 75-90	Kidney , Urinary Bladder , Breast , Liver	Pollution , pesticides in food
Uttarakhand	High 90-105	Neck , Lungs , Breast, Ovrian	Environmental factors, Infection load ,Dietary habits
Himachal Pradesh	High 90-105	Lungs , Cervical	
Jammu and Kashmir	Moderate 75-90	Lungs , Stomach , esophageal	Tobacco consumption, obesity, viral infections, radiation, stress, lack of physical activity, environmental pollutants and genetic factors

Table 1 :- Region wise cancer incidence rate, leading cancer and probable risk factors (data is interpreted from NCBI article, ICMR and NICPR statistics)5

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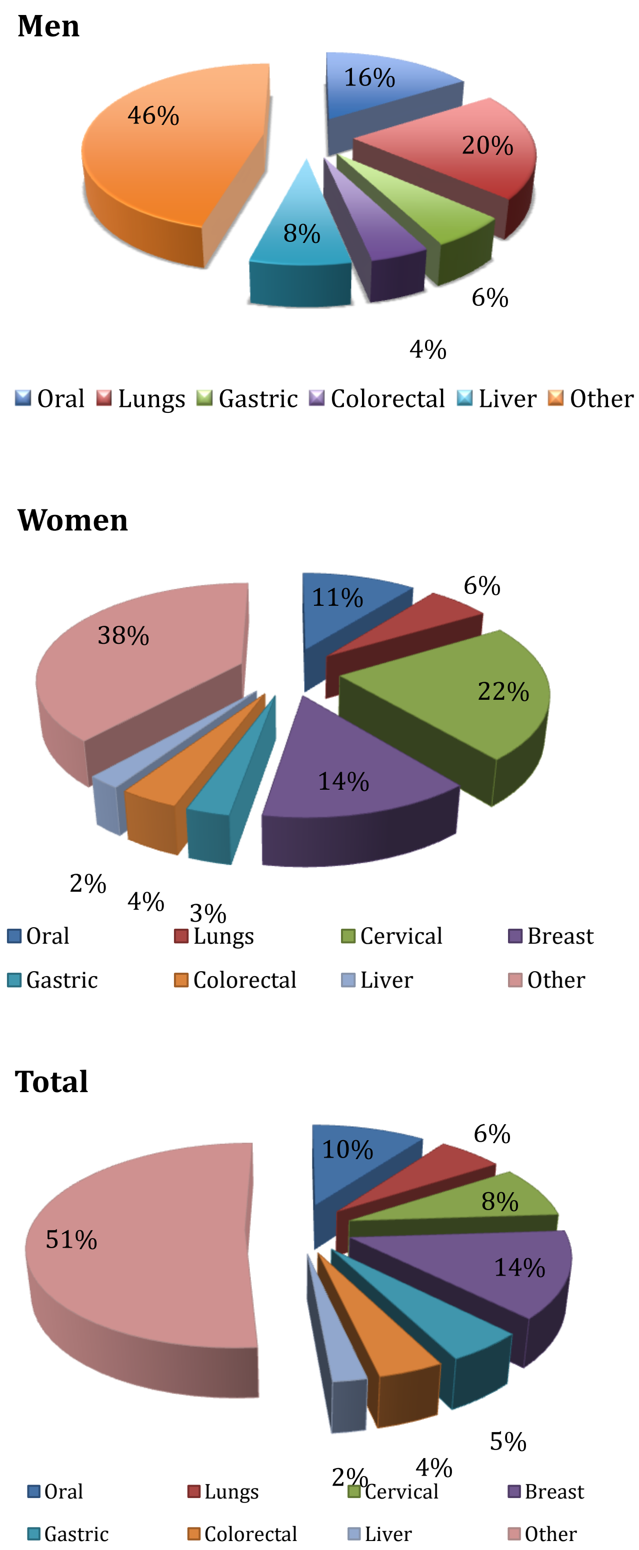

Fig - Cancer statistics men, women and Overall in mix population [35-38]

IV. RELATED WORK

Breast cancer is the most common type of cancer among women. In most Indian cities number patients are increasing, around 25% to 32% of female patients are diagnosed with breast cancer.

A study on the use of learning methods for the detection of breast cancer by Neeraj Dhungal et al. [32] proposed a two-staged learning model, stage one is a multiscale deep belief network with a cascade of classifiers and Gaussian mixture model. GMM is used to select a set of regions representing the candidate's breast mass. The outcome obtained through stage one is processed using deep convolutional network which helps to reduce false-positive regions, finally extracted features and texture are morphologically processed and classified using cascade of random forest classifiers[32].

Results are obtained using state of art dataset INBreast and DDSM-BRCP with improvements as 96% and 75% respectively. It was also learned that keeping false positive rate below 30 per image model works with more efficiency[32,19].

Another research conducted by Sana Ullah Khan et al.[33] used a novel framework based on CNN architecture. In this framework, different low level featured images are processed using well known CNN architectures i.e. GoogleNet, VGGNet, ResNet. These combined features are input to fully connected classifier layers.

Results are verified using dataset obtained from local hospitals which yield 97% of accuracy as compared to used networks which had an average 93% of result positiveness [33].

Lung cancer is another major cancer in India with an increasing mortality rate of 40% among diagnosed patients.

Learning method by BrahimSkourt et al. [34] uses a fully convolutional network. As full convolutional network prons to be slow, this challenge is overcome by upsampling the layers. Furthermore, results are classified using encoder-decoder architecture i.e. UNet.

Another study conducted by Penn Huang et al. [18] used Two ML predictors (ML1 and ML2) which are developed from samples collected from 25,097 participants who had received follow up CT screenings at National Lung Screening Trials (NLST). Double-blinded validation was performed using the Pan-Canadian Early Detection of Lung Cancer Studies (PanCan). The performance of ML predictors was analyzed over Lung-RADS and volume doubling time (VDT) using time-dependent ROC analysis. Data obtained through ML predictors is applied to Lung-RADS in identifying individuals with high cancer risk.

A study on cervical cancer detection by Vidya Kudav et al. [28] used shallow layer CNN for the classification of cervical images. Convolutional kernels and activation maps extract useful features. Pixel wise operations are performed on 2 D image using Rectified linear units which

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changes negative values in activation map with zero. These rectified activation maps ensure faster training of the network. These activation maps are downsampled at the pooling layer by reducing their dimensionality but preserves important information. Now fully connected layer performs classification of the activation map by applying the softmax activation function at the outer layer. All these layers are stacked together to form a convolutional network model which helps to obtain 100% classification accuracy.

A study on Liver cancer detection by Amita das et al. [29] applied a watershed gaussian based deep learning model for effectively classifying liver lesions of liver CT images. Initially, the liver is separated from other organs by applying marker controlled WGDL then the gaussian mixture model is used to segment cancer tissues. A Grey level co-occurrence matrix is used to extract geometrical, textural, and statistical features and are classified using a modified Deep Neural Network.

Oral cancer detection by PandiaRajanjayarajet al.[30] used a partitioned based CNN algorithm to classify tumor images. In his study, he used hyperspectral images of oral cancer patients with image intensity values and texture information. Information obtained using these factors is used to construct the dataset. Data is formulated through the bagging and boosting method. This method combines output from the decision tree and selects final features based on votes of weights. Hyperspectral images of oral cancer patients are considered where image intensity values and texture information gives spatial and spectral information about it. The region of interest is extracted from HSI images by employing complex regression-based training procedures. Pretrainded CNN is modified by the regression-based partition convolution and subsampling layer. Results are verified with SVM and DBN. DBN is a highly precise model for medical image analysis as it contains more hidden layers than fully connected CNN.

In a study done by DmitriiBychkov et al. [29], a deep learning-based classifier is used to predict the five-year survival of CRC patients. Basic morphological features are obtained from a series of CRC stained digitized tumor tissue samples. For testing and training model tumor tissue microarray is prepared from sections of tumor tissue samples. The classifier combines two types of artificial neural network that is concurrent and recurrent. For Clinical markers and visual assessment, the survival curve is prepared by applying the Kaplan-Meier method. The patients are classified as low risk and high risk based on predictors obtained from LSTM MODEL, histological grade, and visual risk score. Obtained results are visually verified and assessed by experts for better accuracy [29].

Author Name	Cancer type	Dataset used	Result	Findings
Neeraj Dhungal et. al[32]	Breast	INBreast and DDSM-BRCT	Used model gave an efficient results as 96 % for INBreast dataset and 75 % for DDSM	False positive results can be reduced by keeping no of images 30. Two staged cascaded R-CNN is used to reduce no of images. More than two staged didn't showed much improvement in results
Sana ullaha Khan et al.[33]	Breast	Dataset of 8000 images is prepared using microscopic images obtained from state hospitals.	yield 97% of accuracy as compared to used networks which had average 93% of result positives	Breast cytology features are extracted using three different architectures GoogleNet ,VGGNet, ResNet and combined together using transfer learning.
Brahim AIT Skourt et al.[34]	Lungs		Accurate segmentation is obtained with dice coefficient index of 0.9502	challenges of full layers convolutional network are solved by up-sampling layers
Penn Huang et al. [23]	Lungs	Dataset obtained from institution NLST and PANCAN	Significant accuracy of 96% after using ML2	ML predictors performed better than Lung-RADS or VDT in stratifying lung cancer incidence and mortality risks. Further a ML tool which recognizes change between spatial and temporal changes and comparative study for changes in nodules and not nodules can improve accuracy in clinical analysis.

Vidya Kudav et al. [28]	Cervical	Dataset obtained from medical colleges at Mumbai and Karnataka by studying 125 patients	The algorithm converges accuracy = 100% and loss = 0.1057 after 250 epochs.	CNN classification accuracy for identifying VIA-positive lesions with shallow layer CNN reaches 100% as the amount of training data Increases. if the size of lesion is relatively small, 1% or 2% of the whole image, the lesion may not be detected by either traditional machine learning or deep learning methods
DmitriiBychkov et al. [29]	Colorectal	Dataset of 641 patients from local hospital. Results are verified by expert through physical assement using other screening methods.	Five year survival rate in low risk group is improved i.e. 65% and in high risk group is 33%	Combine artificial neural network (concurrent and recurrent) applied on small tissue samples obtained from primary tumor by preparing microarray of tissues samples. Ensure five year survival rate to be predicted.
Amita das[30]	Liver	225 CT images collected form IMS and sum hospital in India	Classification accuracy of 98.38% and sensivitiy of 100%	watershed gaussian based deep learning for effectively classifying liver lesions on CT image s of liver.
Pandiarajanjayaraj[31]	Oral	BioGPS UCI repository	94.5 % accuracy over 500 malignant images specificity of 0.98 and sesivitity of 0.94	Regression based partition convolution and sub sampling layer obtained by modifying existing trained network V3 and google inception architecture

Table 2:- Studies conducted by scholars on use of learning method in cancer detection

V. GAP ANALYSIS

In research done by Neeraj dhungal et al. on breast cancer methodology shows significant improvement over other methods. Furthermore, performance can be enhanced when different types of CNN structures along with different filter sizes are used while training datasets. The model is tested and trained on fewer datasets so, results are very much being affected due unavailability of sufficient datasets in later stages.

Sana Ullah khan et al. applied transfer learning on data obtained from the local hospital which can be further tested on state of the art data[33].

In a study on lung cancer detection by Brahim AIT Skourt et al. experiments are based on high-level neural API and Keras with TensorFlow on top of it gave good results but the model was less efficient to segment lung module based on obtained results [34].

Cervical cancer detection by vidya kudav used both the traditional model and CNN to check the performance of the system and concluded that CNN works better on a larger dataset while when the dataset is a modest traditional approach is best. The system misjudged white discharge act white regions and the algorithm misclassified them. The method was also not that efficient to detect lesions of small sizes[28].

In liver cancer detection by Amita das model happens to be less complex due to the use of fewer CT images. As less dataset was processed so traditional approach gave good results but what if the dataset is quite large. The study can be further extended by utilizing the Volumetric size of lesion data to generate 3D visualization of liver tumors [29].

Colorectal cancer study by DmitriiBychkov et al. on duel artificial network to predict the five-year survival rate of CRC patients shows significant improvement. The study was focused on small tissue samples whereas whole tumor cells can be used to generate a dataset for the training models. In the suggested method basic morphological features of CRC stained images where used whereas other features can be included in the study making the model more sturdy[28].

VI. RESEARCH DIRECTIONS

The study proposed by Neeraj dhungal can be extended by a training model for different types of datasets also DBN and multicascaded neural network can be utilized to enhance results. Sana Ullah khan efficiently used three existing CNN architectures to process the data further this CNN architecture with the method proposed can be utilized to generate good results for improvising classification accuracy in breast cancer.

In a cervical cancer detection study by vidya kudav selected smaller patches of size 15×15 which helped to detect smaller lesions by considering this model can be trained to segregate larger tumors also. Miss-classification of regions can be avoided by training model with expert marked acetowhite regions as positive. Liver cancer detection by Amita das et al. results can ve improved by testing the model on larger datasets. The process of detecting tumor can be improved over 3D volumetric images. The volumetric size of the lesion can be obtained by forming 3 D mesh structures formed using slice of images.

An automated model can be made for better medical image processing using deep belief networks. It has fully connected supervised learning structures, it also has the ability to learn feature vectors and can be pretrained for presented input. CRC study by DmitriiBychkov et al. is based on small tissue samples obtained from primary cancer cell study can be further extended by applying it on whole tumor tissue areas as input. Furthermore, the model tested and trained on local patient data which can be utilized to extend the study on real-time data. LSTM activations can be assessed to ensure whether the model is representing morphological entities or not which motivates interpreting the internal behavior of LSTM.

VII. CONCLUSION

In this study, we have attempted to review, assess, and compare the performance of different machine learning models applied for early-stage cancer detection. The major six cancers are reviewed and how learning methods help to improvise their results. We also tried to put cancer statistics for various states in India with their probable causes. The review also gives major cancers causing the maximum mortality rate in that specific state of India. Screening tests are proven to be more useful in the early detection of cancer. With proper screening tests, a patient's life can be prolonged and it helps in a better prognosis. In some cancers, due to screening tests, it became possible for patients to recover from this deadly disease. By incorporating machine learning along with screening tests we can assess patient's data in real-time and can generate more accurate and faster results.

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