Reliability Assessment of Machine Learning in Tumour Detection

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ABSTRACT
It is vital that tumours are diagnosed and predicted early in cancer research to help the patient clinically. In today's world, innovative approaches are being developed to minimise or avoid lethal human diseases. Machine Learning is becoming increasingly popular for classifying cancer patients according to their risk of recurrence. Machine learning expands its applications beyond the technical domain, and its pertinence in the medical area is also proliferating. It can also be used in tumour detection because of its ability to evaluate and classify a large amount of complex image data. Machine learning methods may appear to enhance understanding of tumour progression, but a significant amount of evidence must be obtained to use them in everyday clinical practice. The aim of this study is to review, categorise, analyse, and discuss the current developments in human tumour detection using machine learning techniques which help in cancer diagnosis and cure processes.

Keywords
Machine learning, Deep learning, Neural Networks, Cancer disease, Robotic surgery, Classification, Tumour detection

1. INTRODUCTION
In today's world, health-related diseases like cancer and tumour-related health issues are growing at a rapid rate with very less amount of treatment. It is a huge problem and developed nations are now relying increasingly on Machine Learning algorithms to tackle these problems.

Today Medical imaging analysis is widely used by doctors all over the world to detect cancer and tumour detection at an exceedingly early stage so that people can be treated and cured in the right way. Here Machine Learning comes into play when the computer is shown loads of images and the computer based on the algorithm detects whether the person has cancer or not.

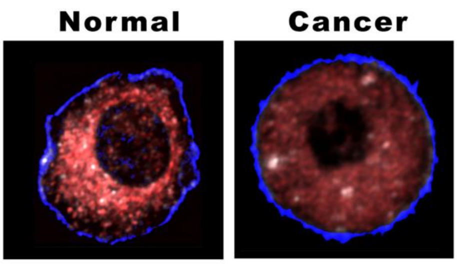

Fig. 1: - Using ultrasound imaging, a normal cell and a cancerous cell are shown. It shows the changes in the cell shape along with changes in protein density and many more changes. [2]

Machine learning (ML) is a type of artificial intelligence (AI) that enables software applications to become more accurate at predicting outcomes without explicitly programming that to happen. Machine learning algorithms forecast new outcomes based on historical data. In artificial intelligence (AI), if a machine's performance in a certain activity gets better with experience, it is said to be learning from prior experiences (data feed-in) with regard to that class of activities [4]. Machine learning algorithms aim to build models based on sample data, known as training data, to make predictions or decisions without explicitly programming them. Machine learning algorithms are employed in various applications where it is difficult or impossible to design custom algorithms, such as medicine, email filtering, speech recognition, and computer vision.

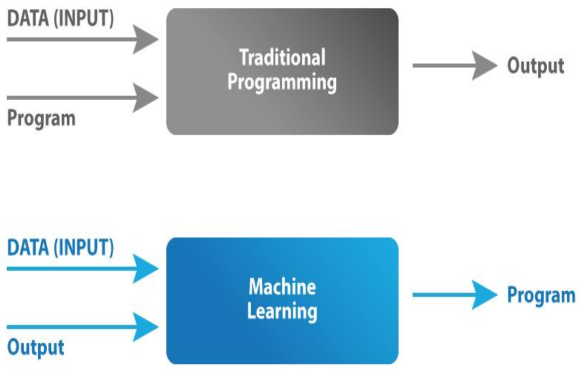

Fig. 2: - Basic diagram of Machine Learning showing its workflow. It focuses on the ability of computers to learn from given data and predict outcomes. [3]

Open AI and DeepMind have made some promising advancements in recent times toward the development of artificial general intelligence [1].

With the deployment of numerous innovative prediction models, the applications of machine learning are expanding in the healthcare industry. This article covers every aspect of machine learning, including its history, evolution over time, healthcare applications, tumour detection, and the dependability and effectiveness of machine learning.

2. HISTORY

History of Machine Learning
A pioneer of computer gaming and artificial intelligence, Arthur Samuel, coined the term machine learning in 1959. [6][7] In explanation-based learning (EBL), Gerald Dejong taught computers to generate general rules based on training data by discarding the non-important data. [8]

History of Tumour Detection

A screening test is performed on people with no symptoms to find diseases such as cancer. George Papanicolaou initially developed the Pap test to study the menstrual cycle. The test became widely accepted as the first cancer screening test. When Papanikolaou realized its potential for detecting cervical cancer early, he presented his findings in 1923, which were met with skepticism from many doctors in the early 1960s. The American Cancer Society (ACS) was the first to promote the test during this time. Screening has since reduced the incidence and mortality rates of cervical cancer by over 50% since screening can detect both cervical pre-cancers and cancer at an early stage. As of 1976, the American Cancer Society formally recommended the use of modern mammography methods. Mammograms are the most reliable way to diagnose breast cancer. [9]

Machine Learning in Medical Care

Detection of Heart Disease

The UCI Machine Learning Repository was considered for this dataset to increase the accuracy of diagnosing heart disease using machine learning techniques [10].

By using Naive Bayes algorithms and Support vector machines, Parthiban and Srivatsa proposed a machine learning algorithm that can detect and analyze heart diseases [11].

To predict coronary heart disease, Otomo has employed Support Vector Machines and Bayes Nets [12].

Analysis of Diabetic Disease

Naive Bayes and Decision trees were used in Iyer's machine-learning method to detect diabetic disorders. Using Naive Bayes gives an accuracy of 79.56% while using a decision tree results in an accuracy of 76.95% [13].

Diagnosis of Thyroid Disorder

It is possible to predict thyroid diseases using machine learning techniques. Using support vector machines and decision trees, a dataset from the UCI repository was used as the basis for classification algorithms [10].

Papandrianos NI and Papageorgiou EI hypothesized advanced approaches for thyroid diagnosis using fuzzy maps based on data mining algorithms [14].

3. LITERATURE REVIEW

Techniques used for classification of tumour

Currently, CNNs are considered to be the best algorithms for automating the processing of images.

Three layers of CNN

Convolutional Layer

This is the initial layer that extracts the distinctive features from the input photos. The mathematical convolution operation is done between the input image and a filter of a specific size, MxM, in this layer. The dot product between the filter and the sections of the input image about the size of the filter is taken by sliding the filter across the input image (MxM).

The output is termed the Feature map, which gives information about the image, such as the corners and edges. Later, this feature map is fed to other layers to learn several other features of the input image.

Pooling Layer

A Pooling Layer is usually applied after a Convolutional Layer. This layer's primary goal is to lower the size of the convolved feature map to reduce computational expenses. This is accomplished by minimizing the connections between layers and operating independently on each feature map. There are numerous sorts of Pooling operations, depending on the mechanism used.

The largest element is obtained from the feature map in Max Pooling. The average of the elements in a predefined-sized Image segment is calculated using Average Pooling. Sum Pooling calculates the total sum of the components in the predefined section. The Pooling Layer is typically used to connect the Convolutional Layer and the FC Layer.

Fully connected Layer

The weights and biases, as well as the neurons, make up the Fully Connected (FC) layer, which connects the neurons between two layers. The last several layers of a CNN Architecture are usually positioned before the output layer.\

In this layer, the input image from the previous layers is flattened and fed to the FC layer. The flattened vector then undergoes a a few more of the same layer processes where the operations of mathematical functions usually occur. During this stage, the classification process begins to take place.

Brain tumour detection technique

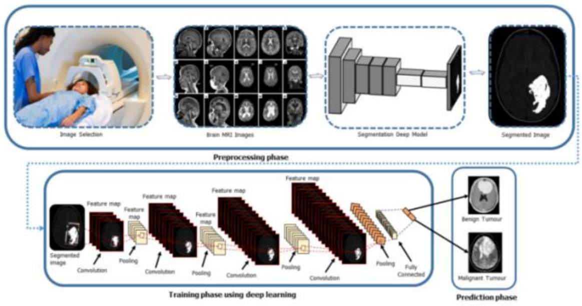

Fig. 3: - Generalised framework for Deep Learning based brain tumour detection. [44]

An aberrant cell clump with four degrees is called a tumour in the brain. Grade 1 and 2 brain tumours tend to grow slowly, while grades 3 and 4 are cancerous (malignant), grow more quickly, and are more challenging to treat [44]. The pre-processing phase is used to reduce noise and non-brain tissues from the input pictures to increase accuracy in the fundamental steps for tumour detection [45]. Organs other than the brain are removed using the brain surface extractor (BSE) procedures. The Wiener filter, partial differential diffusion filter, and fast non-local mean (FNLM) are used to reduce noise. Contrast stretching is used to improve contrast. Fuzzy C-means, k-means clustering, and Otsu threshold approaches are the three most used strategies for segmenting brain tumours. In a similar vein, U-Net architecture is another well-known CNN design used for brain tumour segmentation. Following segmentation, custom characteristics are retrieved to convert segmented images into mathematical descriptions. More reliable techniques are currently being deployed for feature extraction, which is then used for classification. Histogram orientation gradient (HOG), Gabor wavelet transform (GWT), local binary patterns (LBP), and shape-based features were some of the well-known feature extraction methods. For the best feature selection, a genetic algorithm (GA) and principal component analysis (PCA) are utilised, among other feature selection and reduction techniques. CNN architecture is a potent method for detecting brain tumours in recent times. The steps involved in pre-processing, segmenting, training with deep learning, and lastly, making a tumour prediction are shown in Fig. 3. [44]

Lung cancer detection technique

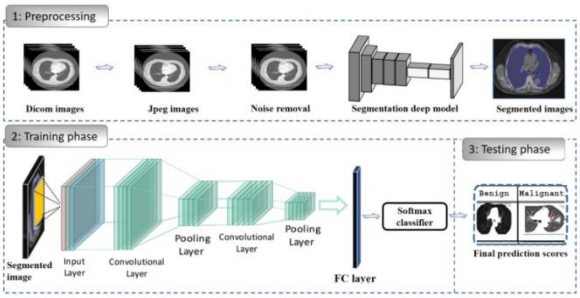

Fig. 4: - Machine supported framework for lung cancer prediction. [44]

The analysis of CT images created using artificial intelligence algorithms enables the early diagnosis and evaluation of lung nodules. These programs, also known as decision support systems, analyze the images using the pre-processing, segmentation, feature extraction, and classification processes shown in Fig. 4. To capture nodular heterogeneity, Multi-Convolution Neural Networks (MCNN) are used to extract discriminating features from alternatively stacked layers. Lung nodule screening and annotation are utilized to assess the LIDC-IDRI method that has been developed. By assembling parallel nodule patches of assorted sizes as inputs, this technique uses three CNN in the MCNN model. [44]

Breast cancer detection technique

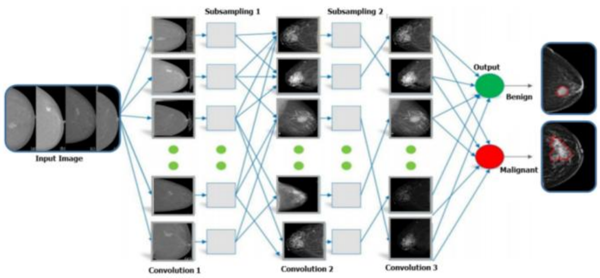

Fig. 5: - Deep convolutional framework process for breast cancer detection. [44]

CNN is one of the best techniques used for detecting breast cancer. As shown in Fig. 5, there are three convolutional layers performing sub-sampling of the input data provided to it. The model segregates tumours into Benign and Malignant categories as output.

Leukemia detection technique

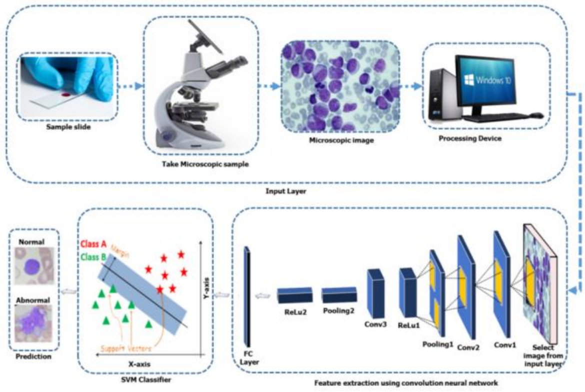

Fig. 6: - Overview of all feature extraction and classification processes for Leukaemia detection. [44]

Segmenting White Blood Cells (WBC) entails separating the cell from its surroundings, frequently by identifying the cytoplasm and nucleus of the cell [46]. Using image processing tools found in medical software is easily accomplished. The literature lists a few steps, including changing the image's colour space and applying morphological filtering, contrast stretching, thresholding, cauterisation, and water-shedding [47, 21]. A binary image of white WBC components may be created because of these actions to conceal the original colour image. Multiple studies have used WBC segmentation to use morphological findings from grey-scale microscopic images. Contrast stretching was done to highlight WBCs' nuclei since their staining is darker than that of other blood components. The WBC sizes were then averaged to create a morphological filter. This morphological filter increased WBC nuclei further and decreased smaller blood components. These procedures yielded highly accurate sub-images with fixed dimensions and centred WBCs. [44]

4. CURRENT DEVELOPMENTS OF MACHINE LEARNING IN VARIOUS TUMOUR DETECTION ALGORITHM

The tabular graph 1. illustrates how accurate each ML algorithm is at detecting tumours. It examines the number of studies conducted on four tumour application areas as well as the various methods used to identify them utilizing specific datasets employed by the authors.

A total of 29 studies are evaluated, with 5 studies on leukaemia and 8 studies each on brain tumours, lung cancer, and breast cancer. The finest outcomes are discussed after the efficacy of each algortihm is compared.

Table 1. Assesment of ML algorithms used in tumour detection

Reference	Application area	Methodology	Datasets	Results Accuracy (%)
Abraham Anderson (Kaggle) [15]	Brain Tumour	CNN, Transfer Learning	BraTS 2019 (Train/Test/ Valid)	98%
Nie et al. [16]	Brain Tumour	3-D CNN with SVM	Self-generated	89.9%
G.Hemanth, M.Janardhan, L.Sujihelen[17]	Brain Tumour	CRF, SVM, GA, CNN	-	89%, 84.5%, 83.64%, 91%
Masoumeh Siar, Mohammad Teshnehlab[18]	Brain Tumour	Feature-extraction CNN-SoftMax	Self-generated	99.12%
Mesut TOĞAÇAR, Burhan ERGEN, Zafer CÖMERT [19]	Brain Tumour	BrainMRNet (Proposed)	Online MRI images	96.05%
Khairandish et al. [20]	Brain Tumour	Hybrid CNN-SVM	BRATS 2015	98.4959%
Ismael et al. [21]	Brain Tumour	ResNet-50	3064-T1 weighted contrast-enhanced MRI	97%
Rehman et al. [22]	Brain Tumour	3-D CNN	BRATS-2015, 2017, 2018	98.32%
Tanzila Saba [23]	Lungs Cancer	Multiple classifiers voting	LIDC	100% 96.97%, 92.67% sensitivity
Firmino et al. [24]	Lungs Cancer	Watershed, HoG, SVM	LIDC-IDRI	97%
Naqi et al. [25]	Lungs Cancer	SVM, CNN, AdaBoost	LIDC	99.2%
A.Asuntha, Andy Srinivasan [26]	Lungs Cancer	Hog, WT, LBP, SIFT, Zernike Moment feature descriptor	LIDC	95.62%
Juan Lyu, Sai Ho Ling [27]	Lungs Cancer	Multi-Level CNN	LIDC-IDRI	84.81%
Cheng-Jian Lin, Shiou-Yun Jeng, Mei-Kuei Chen [28]	Lungs Cancer	2-D CNN with TPO	LIDC-IDRI, SPIE-AAPM	98.83%, 99.97%
Rustam et al [29]	Lungs Cancer	CNN+kernel K-Means	The Cancer Imaging Archive	98.85%
Worku Jifara Sori et al. [30]	Lungs Cancer	Multi-path CNN	KDSB-2017	98%
Anji Reddy Vaka,	Breast Cancer	Deep Neural Network	Various datasets from	97.21%

Badal Soni, Sudheer Reddy K. [31]		with Support value	regional (Andhra Pradesh) and national (India) registries	
Amrane et al. [32]	Breast Cancer	KNN, Naive Bayes	UC Irvine Breast cancer dataset	97.51%, 96.19%
Obaid et al. [33]	Breast Cancer	SVM, KNN, DT	Wisconsin breast cancer dataset	97.67%(avg) 95.1% (avg), 93.23%(avg)
Mahesh Gour, Sweta Jain, T. Sunil Kumar [34]	Breast Cancer	ReHist (Deep residual CNN)	BreaKHis	92.5±2.8%
Wang et al. [35]	Breast Cancer	CNN, US-ELM, ELM	Dataset containing 400 mammograms	86.5%
Zuluga-Gomez et al. [36]	Breast Cancer	CNN	Thermal image database	92%
Karan Gupta, Nidhi Chawla [37]	Breast Cancer	ResNet-50	BreaKHis	93.27%
Latif et al. [38]	Breast Cancer	CNN	Mendeley Breast Ultrasound	88.0%
F Scotti et al. [39]	Leukaemia	HistoTNet(CNN)	Atlas of Digital Pathology	97.92%
Supriya Mandal, Vani Daivajna, Rajagopalan V [40]	Leukaemia	GBDT	The Cancer Imaging Archive	85.6% F-1 Score
Nimesh Patel, Ashutosh Mishra [41]	Leukaemia	K-Means, Zack algorithm SVM	-	93.57%
Rehman et al. [42]	Leukaemia	CNN using AlexNet	Amreek Clinical Lab dataset	97.78%
Zhang et al. [43]	Leukaemia	ARN, CNN, HOG, SVM	Shandong Provincial Hospital + BCCD	95.93%

(CNN:- Convolutional Neural Network, BRATS:- Brain Tumour Segmentation, SVM:- Support Vector Machine, CRF:- Conditional Random Fields, GA:- Genetic Algorithm, ResNet:- Residual Neural Network, LIDC:- Lung Image Database Consortium, HoG:- Histogram of oriented Gradients, LBP:- Local Binary Pattern, SIFT:- Scale Invariant Feature Transformation, TPO:- Taguchi Parametric Optimization, SPIE:- Society of Photo-Optical Instrumentation Engineers, AAPM:- American Association of Physicists in Medicine, KDSB:- Kaggle Data Science Bowl, DT:- Decision tree, ELM:- Extreme Learning Machines, GBDT:- Gradient Boosting Decision Tree, BCCD:- Blood Cell Count and Detection)

5. RESULTS

Brain tumour

For brain tumours, it could be inferred that CNN-SoftMax with Feature-extraction works the best and gives a 99.12% accuracy, as shown by Masoumeh Siar and Mohammad Teshnehlab[18].

Lung Cancer

For lung cancer, it could be inferred that a 2-D CNN with TPO gives the highest accuracy of 99.97% on the SPIE-AAPM dataset, as shown by Cheng-Jian Lin, Shiou-Yun Jeng, and Mei-Kuei Chen [28].

Breast Cancer

For breast cancer, it could be inferred that a Deep Neural Network with Support Value gives the best accuracy of 97.21%, as shown by Anji Reddy Vaka, Badal Soni, and Sudheer Reddy K [31].

Leukemia

For leukemia, it could be inferred that a network called HistoTNet, which is based upon CNN, gives the best accuracy of 97.92%, as shown by F Scotti et al. [39].

6. CONCLUSION

In recent decades, technological advancements have resulted in a significant decline in the mortality rate of cancer patients. One of the primary reasons for this decrease is the use of advanced imaging techniques like MRI scans and other tools that are much more effective in detecting tumours at an early stage. Artificial Intelligence and Machine Learning are making incredible progress, and doctors are implementing these machines to diagnose and treat illnesses at an early stage. In accordance with the WHO's "Guide to cancer early diagnosis" policy, it has been observed that early detection enables 30-50% of cancers to be prevented. From our assessment, it is much clearer how Deep Learning techniques can provide greater accuracy when predicting several types of cancer and tumour in the future.

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