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Deep learning models for early detection and diagnosis of cancer from medical imaging

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Abstract
The most deadly kind of cancer for women globally is breast cancer. Since the cause of breast cancer is unknown, there are currently no proven methods for treating or preventing the condition. Breast cancer can be successfully detected and managed with early diagnosis, and there may be a higher chance of full recovery with early detection. Early detection of breast cancer is best achieved via mammography. This device also makes it possible to identify other diseases and could reveal details regarding the type of cancer, such as benign, malignant, or normal. This article explores an evolutionary technique for categorizing and detecting breast cancer that is based on machine learning and image processing. This model helps with the classification and detection of skin diseases by combining machine learning, feature extraction, feature selection, and image preprocessing approaches. A geometric mean filter is applied to improve the quality of the picture. AlexNet is employed in feature extraction. The relief algorithm is used to pick features. The model uses machine learning techniques such as random forest, KNN, least square support vector machine, and Naïve Bayes for disease categorization and detection. This proposed technology is advantageous for accurately identifying breast cancer disease using image analysis.

Keywords: Mammography, LS-SVM, KNN, random forest, naïve Bayes

Introduction

Known as a malignant tumour, cancer is defined as a group of diseases that includes more than 200 pathologies. Cancer is characterized as a malignant tumour, and unlike an individualised disease, it is characterised as a group of illnesses whose malignant abnormal cells, typically very aggressive, grow uncontrollably, invading adjacent organs and tissues, and can spread throughout the body giving rise to tumours in other regions. The so-called metastasis is present in this propagation case. Prior to developing into cancer, these cells were healthy; however, when their functionality was damaged, they developed deformities, which caused them to procreate more quickly and disorderly with an increase in glucose consumption [1]. The sickness is an unbalanced, aberrant state of the body or mind. Cancer is one of the illnesses that terrifies people the most and leaves them confused about the future. This long-lasting negative reductionism, which was deeply ingrained in the cultures of civilizations, terrified many people who could not even pronounce the word "cancer." With modern medical technology, this thinking has shifted because there is a prospect of recovery if therapy is initiated quickly [2]. Any area of the body could be impacted by the growth of malignant cells. As the malignant growth grows throughout the body, normal cells are squeezed out, making it challenging for the body to function normally [3]. The start of breast cancerous growth is the abnormal cell development. These cells frequently form knots or x-beams, which are hallmarks of tumours. If the cells within tumours develop into new, more potent substances or spread throughout the body, tumours may be dangerous (diseases). Breast cancer can spread to different areas of the breast. The milk ducts are where the majority of breast cancers start before moving to the areola. Some of them have their roots in the milk-producing organs. There are numerous ways that breast cancer can develop, some of which are more frequent than others. There are a few types of breast cancer that develop in particular tissues [4].

Using the computer-aided design framework, colon polyps and malignant breast and lung development can be categorised. However, these modalities can still be used if the master human audience is not present.

Computer-aided design frameworks were utilised to show radiologist regions that appeared to be anomalies using a compilation of patient drawings. Because CAD can behave differently based on the settings, we should keep this in mind and make any required adjustments to obtain the most accurate results [5]. The majority of CAD architecture is created to assist researchers in becoming more accurate and proficient. They might be distracted by a few highlights and miss an injury if they are attempting to distinguish between prescribed infections. Mammograms have a wide variety of viewpoints, thus it happens frequently that one of them will divide an identical instance in order to get a different result. In contrast to radiologists, who must support outcomes, CAD frameworks handle pictures more quickly without compromising accuracy [6].

This article proposes an evolutionary method for identifying and classifying breast cancer that uses machine learning and image processing.This model classifies and detects breast cancer using picture pre-processing, image enhancement, segmentation, and machine learning methods.

Literature Survey

Keeping track of cancer data is crucial because it demands long-term planning, potential education, and ongoing monitoring of each cancer patient [7]. The purpose of this study is to demonstrate how data mining techniques may be utilized to enhance cancer log data statistical analysis findings. The Greece Cancer Log was used to collect data between 1998 and 2004. The data was prepared for analysis by being processed and trained using algorithms and data mining techniques. The authors have created a way for gathering and analyzing current cancer data using data mining techniques, and they anticipate that additional researchers will find this method to be helpful in the future.

Tan *et al.* [8] created and evaluated a novel computer model for predicting the risk of breast cancer in the near future on the basis of the quantitative analysis of bilateral mammographic picture element distinctions within the collection of negative full-field digital mammography images. The historical dataset consisted of 335 women's digital mammograms from four different time periods. Three support vector machine risk replicas have been built and weathered with the use of leave-one-instance-out-based cross-validation. The findings demonstrate a mammographic feature distinction-based risk model and an increasing pattern of the near-period risk for breast cancer detected by mammography.

In this paper [9], two well-known datasets under machine learning are extracted using evolutionary optimization strategies by using four alternative optimization methodologies. The suggested optimization techniques were examined using the e Iris and Breast Cancer datasets [28]. In this article's classification problem, a neural network is combined with four optimization techniques: the dragonfly, grey wolf, whale, and multiversity optimization [29]. A number of control metrics were taken into account in order to reach a precise conclusion. According to the proportionate study, grey wolf and multiversity provide exact results over the other two approaches in terms of convergence, runtime, and classification rate [30].

The advancements in computer-aided breast cancer diagnosis since the study's [10] commencement have been examined in a systematic review. The systematic review might be applied to a wide variety of papers in the field by using a wide range of technical databases as a reference. However, the article's focus was strictly on scientific and academic publications, and it didn't take into account any commercial factors [36]. The survey's findings give a general overview of the state of computer-aided diagnosis systems today in regard to the picture modalities and machine learning classifiers that are being employed [37].

Breast cancer is the second most frequent type of cancer worldwide, behind lung cancer, claim Mohant y, S.S. and Mohant y, P.K [11]. In 2016, about 650 million people were obese, making up the roughly 1.9 billion overweight people worldwide. As a result, it is obvious that obesity and the risk of breast cancer are closely related [38].

The author of this review indicates that oestrogen generation through body fats is a peripheral location for oestrogen biosynthesis and oestrogen disclosure impacting body fat circulation.

According to Wang *et al.* [12], accuracy in breast cancer detection and decreased diagnostic variance are crucial. The authors provide a novel model called WAUCE (weighted area under the receiver operating characteristic curve ensemble), and using data from Wisconsin diagnostic centers, they compare its performance to that of earlier models. The proposed method detects breast cancer with considerably reduced variance and improved accuracy when compared to existing ensemble models. The authors propose this approach for the diagnosis of various illnesses as an enhanced and more reliable alternative.

The deep learning-based classification of breast tissues from histology images, according to Yang *et al.* [13], has low accuracy due to a lack of training data and understanding of structural and textual data that can span multiple layers. Haematoxylin-eosin stained breast microscope pictures are divided into four groups using the multiscale convolutional neural network (EMCN) approach provided in this paper: benign lesion, normal tissue, invasive, and in-situ malignancy. Each image is translated to numerous scales before training the pre-trained models, such as ResNet-152, DenseNet-161, and ResNet-101. During each scale, the collected training bits are then put to work and improved. The EMS-net technique outperforms the other three examined algorithms in terms of accuracy [31].

The manual segmentation of ultrasound pictures, according to Xu *et al.* [14], requires a substantial investment of time, necessitating automatic segmentation. Using convolution neural networks, as the authors did, it has been recommended that images of breast ultrasound be separated into four groups: mass, skin, fat, and fibrous glandular tissue [32]. The quantitative measurements and the Jaccard similarity index reveal that the suggested technique performs impressively better than the alternatives by a factor of 80%. The proposed technique might offer the necessary segmentations to aid in the medical analysis of breast cancer and enhance imaging for various forms of medical ultrasound [33].

The work [15] concentrated on many ensemble approaches that are frequently utilised in the field of bioinformatics to carry out prediction tasks. Nine features are examined when looking at ensemble classification techniques for breast tumours, including publication domains, agreed-upon medical activities and research categories, recommended ensembles, the only methodologies used to build the ensembles and the validation structure adopted to look at these ensembles, tools used to build the ensembles, and optimising [34]. Each of the databases for IEEE Explore, Scopus, ACM, and PubMed contained a total of 193 items that were published after the year 2000. The diagnosis remedial job, followed by the experimentally-focused empirical form and evaluation-based research processes, seems to be the one that is most frequently studied among the six medical vocations that are offered [35].

Kakti *et al*. [16] showed improved accuracy in diagnosing breast cancer situations within the datasets [39]. The MMDBM (mixed mode database miner) algorithm is based on supervised learning in the hunt and decision tree algorithms. The proposed technique produces results that are more precise since they are based on empirical learning and comparison analysis. The author's suggestion to include other datasets and attributes could produce even more effective outcomes.

Ting *et al*. [17]. advised using an approach known as convolutional neural network improvement for breast cancer classification for breast cancer detection. In order to aid medical experts in the diagnosis of the condition, it uses the convolutional neural network to improve the classification of breast cancer lesions. The CCNI-BCC algorithm enables classification of medical imaging as benign, malignant, or healthy patients [40].

Early detection and classification of breast cancer, according to Chaudhury *et al*. [18], can assist patients in receiving the proper care. The authors have presented a new deep learning framework for the diagnosis and classification of breast cancer utilizing breast cytology pictures using the notion of transfer learning. Transfer learning tries to use the knowledge learned from one problem to tackle a similar problem in the future, in contrast to present learning paradigms. For the classification of malignant and benign cells using the average pooling classification method, an attribute-mining structure is proposed that makes use of CNN architectures like Google Net, VGGNet (visual geometry group network), and residual networks that have previously been trained and fed into a completely linked layer. The diagnosis of breast cancer has been the subject of related studies [19-21].

A network model has been created by the authors to categorise medically related data. Additionally, security procedures are being developed to protect wireless sensor data related to medicine.

Methodology

Before you begin to format your paper, first write and save the content as a separate text file. Complete all content and organizational editing before formatting. Please note sections A-D below for more information on proofreading, spelling and grammar.

Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

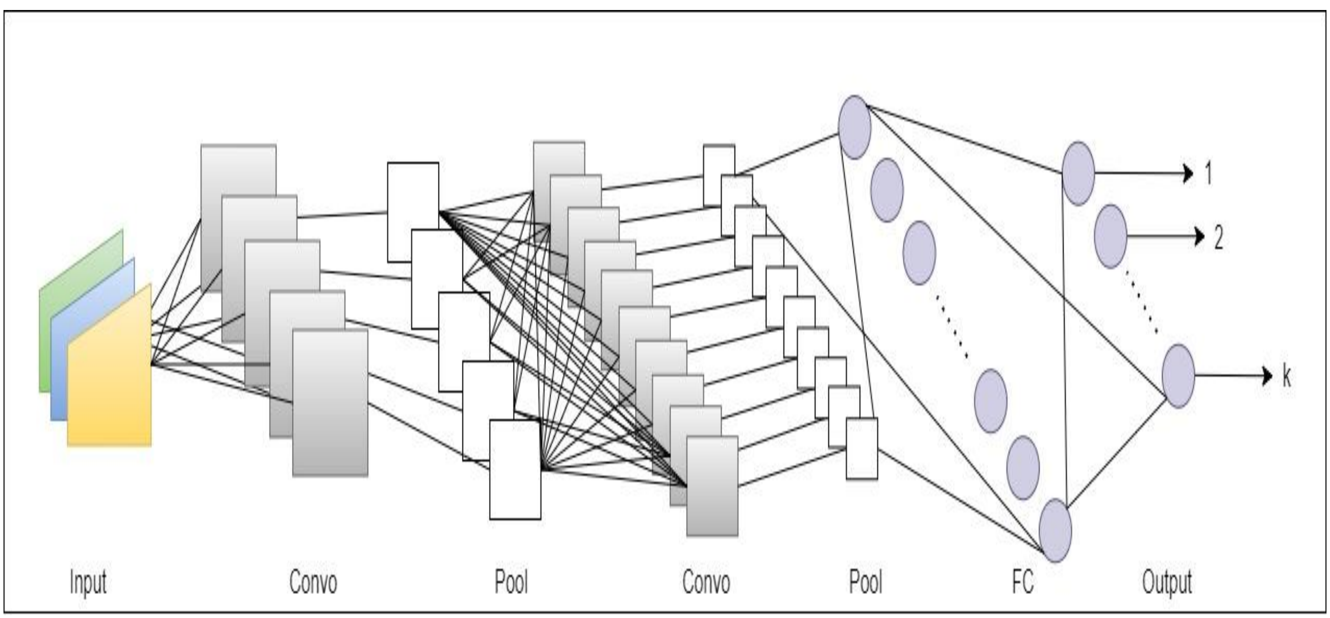

Fig 1: CNN basic architecture

A. Overview of Convolutional Neural Networks

In recent years, convolutional neural networks (CNN) have emerged as a particularly promising deep learning technology. Convolutional layers, which have their roots in image processing, are widely used and frequently demonstrate great effectiveness in practically all deep learning subfields.

Because of CNN's ability to extract features, recognise patterns, and classify data, it has been used in many applications recently.

The two fundamental components of CNN's design are a classifier and a feature extractor. In turn, the feature extractor is made up of multiple connected layers. Convolution layer (Conv), pool layers, activation function, and fully connected layer are all components of CNNs [10].

CNNs have demonstrated remarkable success in a variety of image classification and object recognition tasks in recent years, mostly attributed to their capacity to learn extremely complicated aspects of picture data. The most popular deep learning methods used for computer vision applications in the literature today are CNN-based.

CNNs can also be classified as fully convolutional networks (FCA). FCA architectures are eventually devoid of completely connected layers; they just have convolution and pooling layers (perhaps with deconvolution and upsampling layers as well). Typically, an FCA's input and output have the same dimensions. These intense prediction models have significantly increased both efficiency and accuracy for segmentation/segmentation jobs. A CNN example architecture is shown in Figures 1.

B. Methodology

The methodology is divided into the following main sections. The suggested model's block diagram is shown in Figure 2.

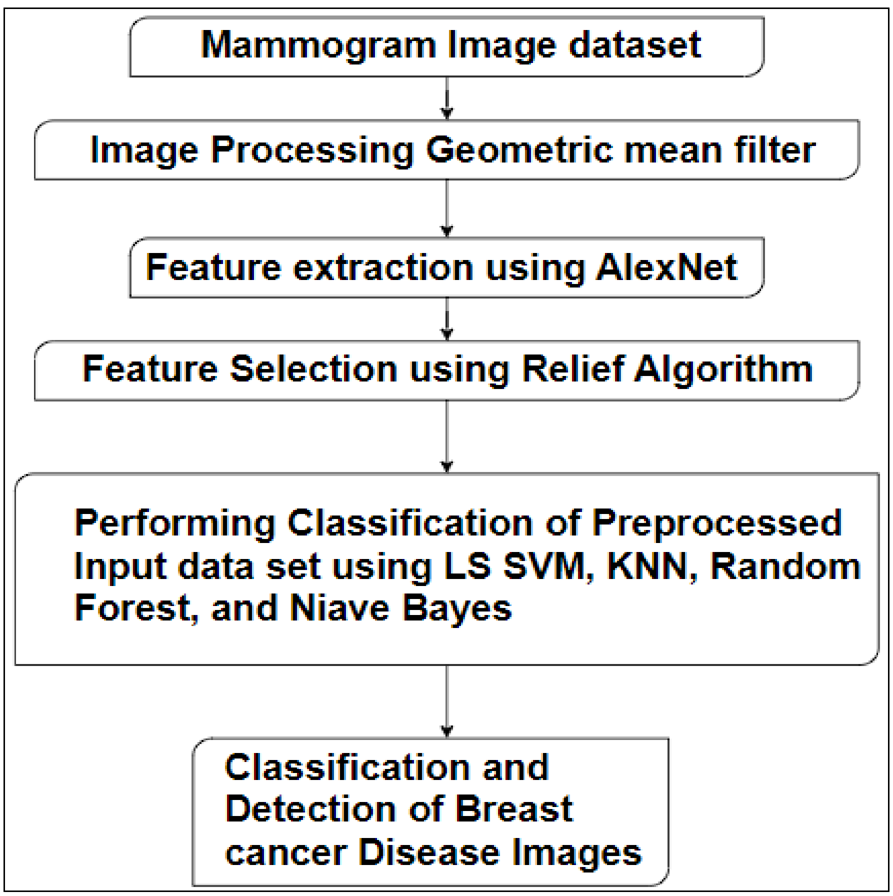

Fig 2: Technique for mammogram image classification and detection of breast cancer

- Image processing using filter.
- Feature extraction using AlexNet.
- Feature selection using relief algorithm.
- Classification using LS-SVM and other algorithms.

The proper classification of illness pictures requires image preprocessing. Images from mammograms contain a variety of noise. Image filtering techniques are employed to eliminate these sounds. The input photos are filtered using a geometric mean filter to eliminate noise [22, 23].

Deep learning is the method that AlexNet use to extract features. Using an AlexNet CNNfully connected layer, features are extracted from the concatenated image. The AlexNet CNN has 22 transfer learning-based feature extraction layers in addition to a fully connected (FC) layer with 1×1×64 dimensions.

The original relief algorithm was developed by Kira and Rendell, who were inspired by instance-based learning approaches. Each feature is assigned a proxy statistic by relief's feature selection filtering process, which can be used to assess the feature's "quality" or "relevance" to the goal notion. Due to its exclusive design for binary classification problems, the initial relief approach was unable to address missing data [15].

SVM and LS-SVM are two varieties of supervised learning techniques. These provide machine learning assistance for situations involving regression and classification. The SVM and LS-SVM function as binary linear classifiers that are non probabilistic [26]. They construct a line known as a hyperplane, which divides the two classes. In addition to SVM, LS-SVM is used to find a training model for classification tasks as well as to solve linear equations. While LS-SVM is used to solve linear equations, SVM is utilised to solve quadratic equations [27].

Compared to SVM classifier, LS-SVM classifier is more affordable. Because LS-SVM just requires the solution of a set of linear equations to function, it is far simpler to utilize than SVM. There are very few parameters in LS-SVM that need to be set. Other multivariate classifiers exist, such as the NN and NB classifiers, but LS-SVM performs more well when handling both linear and nonlinear multivariate classification. Among the kernels utilized in LS-SVM classifiers are linear, polynomial, quadratic, radial basis function (RBF), and MLP kernels [24].

The KNN classifier is among the most basic classifiers. We refer to it as a "lazy" algorithm. An algorithm that does not make any assumptions on the distribution of the data is called a nonparametric algorithm. This is not done by a KNN classifier. Using information from its closest neighbor, the KNN method is utilized to determine the appearance of the unknown pattern. The nearest neighbor classifier is used to classify the images. A KNN classifier consists of these two components. The first step is to calculate the distance between each image used in the training phase and the unknown image. The second step is determining which training photos are most likely to be test images is the second step. Both the distance between the items and their classification are determined using the Euclidean distance. The most often used method for determining the separation between two places is the Euclidean distance. The square root of the total distance between the two places is what it is [25].

One popular method for carrying out supervised learning is NB classification. The underlying premise of the Bayesian theorem is that every set of features is distinct from every other set.

The term "person who wants to learn" is another name for an NB classification. It seems to be really simple to grasp and very easy to develop. Here's a quick method to determine the test data's anticipated class. It handles large amounts of data as well. This classification approach determines a conditionall probability for the relationships between attribute values and the class by examining the relationships between each attribute and the class for each unique case. During training, it is utilized to calculate the likelihood of each class by calculating the number of times the training dataset appears at various times [41].

The RFT classifier is a technique for group classification that uses random forests. It is equivalent to using the nearest neighbour classifier technique. FT selects variables at random, which leads to a higher number of trees. A classifier gains knowledge by dividing tree nodes based on a random subset of data attributes. The bagging principle, which states that each subsequent tree is constructed using a bootstrap sampling of the data items, is the foundation of the RFT classifier. The data elements are categorized by means of a majority vote.

Result Analysis

After completing the whole process of model building, it is time for results. The parameters which are used to compare the performance of different algorithms are-

- Accuracy: The accuracy metric is one of the simplest Classification metrics to implement, and it can be determined as the number of correct predictions to the total number of predictions.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

- Precision: The precision metric is used to overcome the limitation of Accuracy. The precision determines the proportion of positive prediction that was actually correct. It can be calculated as the True Positive or predictions that are actually true to the total positive predictions (True Positive and False Positive).

$$\text{Precision} = \frac{(\text{TP})}{(\text{TP} + \text{FP})}$$

- Recall or Sensitivity: It is also similar to the Precision metric; however, it aims to calculate the proportion of actual positive that was identified incorrectly. It can be calculated as True Positive or predictions that are actually true to the total number of positives, either correctly predicted as positive or incorrectly predicted as negative (true Positive and false negative).

$$\text{Sensitivity or Recall} = \frac{(\text{TP})}{(\text{TP} + \text{FN})}$$

Where TP = True Positive, TN = True Negative, FP = False Positive, and FN = False Negative

Table 1: Performance Metrics

Confusion matrix results	Accuracy	Sensitivity	Precision
TP	0.9610	0.9521	0.9647
TN			
FP			
FN			

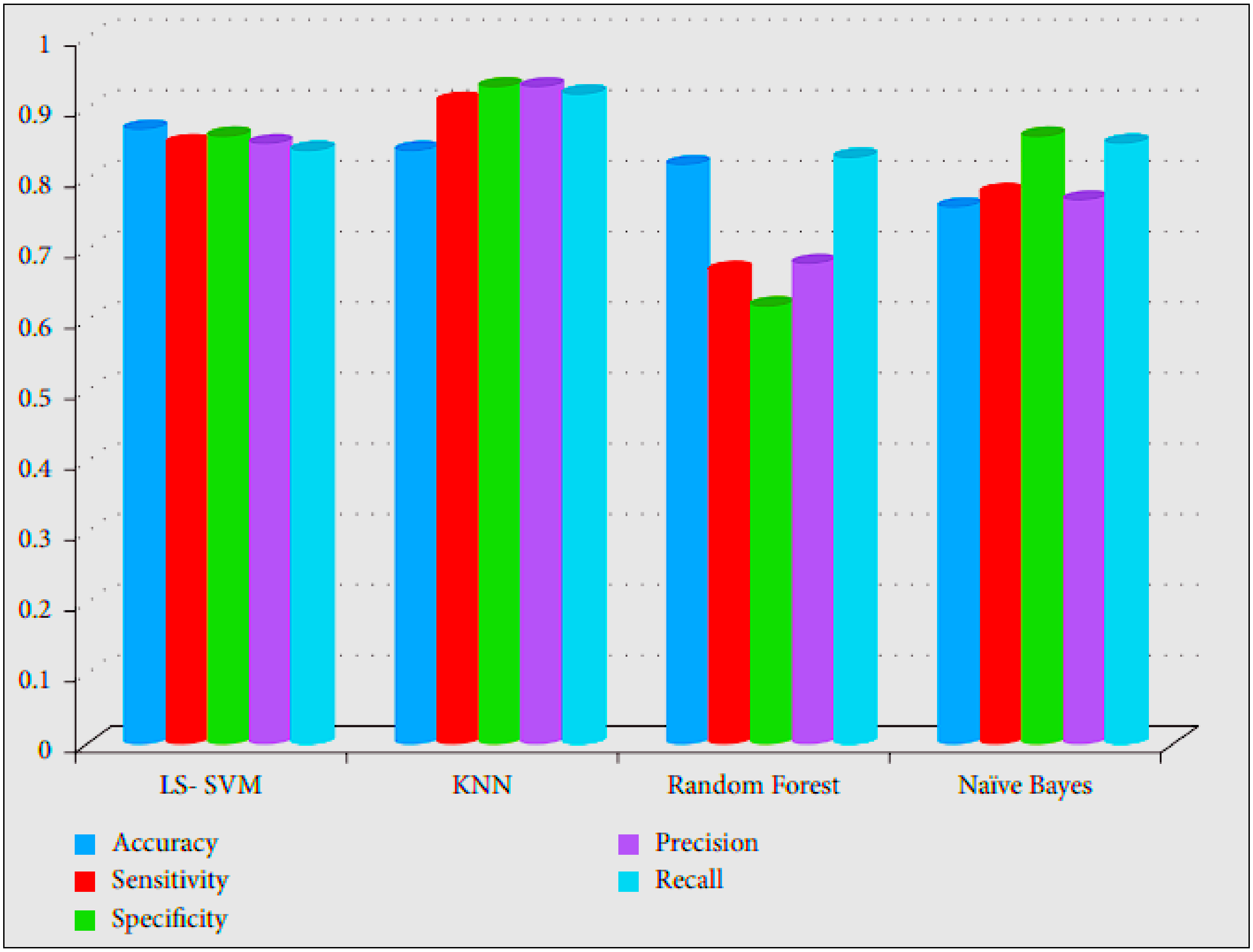

Fig 3: Result comparison of classifiers for breast disease detection with feature selection.

Conclusion

Breast cancer affects one in every eight women globally and is the most deadly type of cancer for women. Breast cancer cannot currently be prevented or treated with any efficacious treatment because its aetiology is yet unknown. Early diagnosis and treatment of breast cancer are very effective methods of both diagnosing and treating the disease, and early discovery may increase the likelihood of full recovery. The most reliable technique for identifying breast cancer is mammography, which can be used to detect it early [42].

The ability to identify additional ailments and provide information on cancer types, such as benign, malignant, or noncancerous, are secondary benefits. For the first time, an evolutionary method based on image processing and machine learning has been developed to classify and identify breast cancer. Through the use of machine learning, feature extraction, feature selection, and image preprocessing techniques, this model can help with the categorization and detection of skin conditions. To enhance the overall quality of the image, apply the geometric mean filter. AlexNet is used to extract features from the data. The relief algorithm is used to select the properties that will be used [43]. The model uses machine learning methods including KNN, random forest, least square support vector machine, and Naive Bayes to identify and classify different disorders. One major feature of the suggested method is its ability to accurately identify breast cancer disease using image analysis.

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