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A Systematic Survey of Classification Algorithms for Cancer Detection

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ABSTRACT

Cancer is a fatal disease induced by the occurrence of a count of inherited issues and also a count of pathological changes. Malignant cells are dangerous abnormal areas that could develop in any part of the human body, posing a life-threatening threat. To establish what treatment options are available, cancer, also referred as a tumor, should be detected early and precisely. The classification of images for cancer diagnosis is a complex mechanism that is influenced by a diverse of parameters. In recent years, artificial vision frameworks have focused attention on the classification of images as a key problem. Most people currently rely on hand-made features to demonstrate an image in a specific manner. Learning classifiers such as random forest and decision tree were used to determine a final judgment. When there are a vast number of images to consider, the difficulty occurs. Hence, in this paper, weanalyze, review, categorize, and discuss current breakthroughs in cancer detection utilizing machine learning techniques for image recognition and classification. We have reviewed the machine learning approaches like logistic regression (LR), Naïve Bayes (NB), K-nearest neighbors (KNN), decision tree (DT), and Support Vector Machines (SVM).

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1. INTRODUCTION

Cancer is becoming one of the dominant reasons of death among teenagers around the world. Lung, breast, stomach, and prostate cancers are among the frequently detected cancers in males and females, and if not found early, they can cause serious complications or even death. Cancer is the abnormal development of cells in the human body. According to research, a healthy person can be affected by nineteen distinct types of cancer. Lung cancer has the greatest fatality rate of any of these tumors. It is estimated that 1.7 million individuals die every year as a consequence of this disease [1].The primary reason of lung tumor has been identified as smoking that accounts for about 80% of all lung tumor occurrences globally. Early-stage lung cancer is harder to identify. As per the research, almost 25% of patients infected with the disease in its beginning phases showed no indications. Because lung cancer cannot be seen with the bare eyes, unlike other malignancies, its indications are commonly misinterpreted as bronchitis, asthma, or coughing. When a patient's chest is X-rayed or a CT scan is performed for any other reason, lung cancer is frequently detected [2].The remaining 75% of persons are diagnosed after they begin to feel or develop symptoms. Such indications could be caused by the primary tumor's direct impacts, tumor which has progressed to alternate areas of the body, or hormonal, circulatory, or other systemic abnormalities. The natural flow of lymph that is directed outward from the lung and inward towards the center of the chest causes the lung tumor to progress into the middle of the chest [3]. When tumor strikes, a single tissue or a group of tissues begins to multiply uncontrollably and disorganized, leading to the production of cancers if not prevented. Any cancer shall be classified into one of two types: benign or malignant. Malignant tumors, in contrast to benign tumors, penetrate adjacent body tissues and shall progress to other body areas as they grow. Normally, benign tumors aren't considered hazardous, but they can become dangerous if they acquire critical structures like blood arteries or nerves that are required for their growth [4]. The tumor is termed to be invasive if the discussed pattern is followed, and radiologists and other healthcare experts employ different imaging tools to detect it. Numerous machine learning algorithms, particularly neural networks, were broadly applied for lung cancer identification utilizing medical pictures in recent years. Many of the offered methods have a high rate of accuracy [5].

2. IMAGE PROCESSING TECHNIQUES

The study [6] has presented a contrast constrained adaptive histogram equalization approach for picture pre-processing (CLAHE). They extracted picture features employing the gray-level co-occurrence matrix (GLCM)that also provides details regarding the position of pixels with same gray-level numbers. A GLCM shall have a number of statistical properties, which shall be retrieved and used for analysis. For finding the best features, the authors employed automatic feature selection techniques. The study [7] used the picture dataset from mammograms to forecast the risk of acquiring breast tumor in the future. To compute image feature asymmetry, the proposed approach is built around four image processing elements: image preprocessing, segmentation, feature extraction, and categorization. The images were processed using (i) preprocessing and (ii) feature extraction algorithms [8]. Image enhancement and picture segmentation are the two key components of the image pre-processing procedure. They examined three methods for enhancing the images: Gabor filtering, automatic enhancement, and fast Fourier transform. They discovered that the Gabor filter is the most appropriate method for enhancing the images through their tests. They employed thresholding and watershed segmentation approaches for picture segmentation, and they discovered that watershed segmentation outperforms thresholding. The work [9] achieved comparable findings by employing the same picture enhancement techniques. For feature extraction, they used a binarization and masking strategy and extracted four characteristics from the image: mean intensities, area, perimeter, and eccentricity. Likewise, the article [10] used picture segmentation algorithms based on watershed approaches. For extracting the characteristics from the region of interest, they employed feature extraction laws. They suggested a number of different image processing algorithms for enhancing the images, preprocessing, segmenting, and extracting the features. The purpose of [11] was to employ a simple Otsu's technique for picture segmentation, as well as a morphological opening technique and a periodic line as a fixed-size structuring component. The approach of Otsu minimizes intra-class variance while also minimizing inter-class variances. They've also discovered a main flaw in using Otsu's technique: Even after transforming the gray scale images to binary, certain spaces in the lung remains that corresponds to artery or air in the lung region, and those spaces may lead to classifier predicting false numbers by giving the appearance of a malignant tumor. They suggest that structural mechanisms be employed to cover the spaces left after utilizing the thresholding technique on grayscale CT scan images to solve this issue.

3. MACHINE LEARNING MODEL

The field of artificial intelligence revolves around machine learning. Probability theory, demographics, approximation hypothesis, convex assessment, algorithmic complexity theory, and other fields are all involved in this multidisciplinary transdisciplinary field. A branch of computer science concerned with how computers model or apply human learning performance in order to gain newer abilities or information and restructure available knowledge frameworks in order to enhance their overall effectiveness. Machine learning, generally, is the process of learning laws from a huge amount of historical information using similar algorithms, making predictions or assessments on newer data sample, and then learning like humans. The majority of machine learning approaches work with information that has a deep framework. Such physical models comprise only one or two units of non-linear feature transformations at most, resulting in a framework with only one hidden unit or none at all.

3.1. Types of machine learning

There have historically been three major objectives in machine learning: supervised, unsupervised, and reinforcement learning [21].

3.2. Supervised learning

This type of machine learning may be accompanied by someone, such as a professor, who assists the learning process. As a consequence, create a database that serves as an instructor, with the goal of training the machine or framework. When fresh information is input to the system after it has been developed, the system may execute producing a forecast and making the decision.

3.3. Unsupervised Learning

By observing the observations, this framework is able to identify structures in the information. It can construct some clusters in a dataset that is provided to it by autonomously finding certain patterns and relationships. However, the model is unable to add a label to clusters; it cannot, for example, indicate that the clusters contain vegetables or fruits, but it can distinguish between vegetables and fruits. The data set, for example, shows images of cars, trucks, and planes that are presented to a framework, and the framework will make clusters based on specific structures and relations, and then divide the data set into those clusters. In the future, if new data is fed into the model, it will be processed in one of the previously built clusters.

3.4. Reinforcement learning

An agent can determine what would be the perfect result, based on its interaction with the surroundings. As part of this strategy, the agent uses trial and hit. In this model, the agent is rewarded with one point for a correct answer, or penalized with one point for a wrong one, and based on the correct reward points the agent receives, the model is trained itself. As the model is being trained, it will then be able to make predictions in relation to new data [22].

3.5. Deep learning

Machine learning has a sub-discipline termed deep learning. It's a subfield that focuses on self-learning and improvement through the use of computational models. While machine learning makes use of simple ideas, deep learning makes use of a variety of neural network models that are built to mimic how a human learns and perceives. Till now, the intricacy of artificial neural networks was limited solely by the computer power available [23]. Larger, more complicated neural networks have been enabled by advances in big data analytics, permitting computers to perceive, study, and respond to complicated matters much faster than a human. Picture categorization and language translation have been made easier with deep learning.

3.6. Semi-supervised learning

The goal of this subset of machine learning is to use both labeled and unlabeled data in order to achieve particular learning objectives. For example, it can be used to take advantage of the enormous amount of unlabeled information accessible in severalutilization scenarios, along with smaller classes of labeledinformation, in supervised learning. An example of how unlabeled data can be used for categorization is shown in Figure 1.

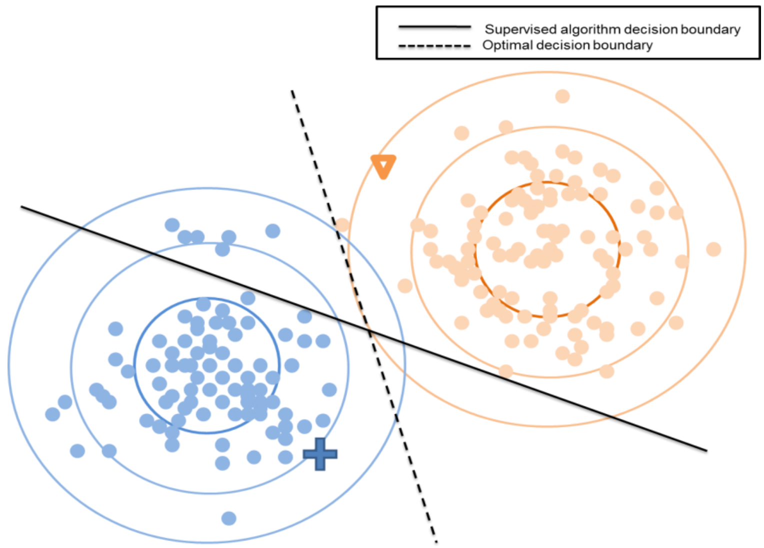

Figure 1. An illustration of binary classification in the context of unlabeled information. Unlabeled points are colored based on their genuine labels. Each of the three standard deviations of input data is represented by a different colored, unfilled circle.

They examined two-class artificial classification task. 100 samples are taken from a two-dimensional Gaussian dispersion with equal covariance matrix for both classes. After that, one sample from each class is used to create the labeled data set. Any supervised learning algorithm will almost certainly use a solid line that is normal to the line segments linking the two labeled datapoints and crosses it in the middle as the decision boundary. However, this is a long way from the best choice point. As seen in this picture, the clusters deduced from unlabeled data will substantially aid us in defining the decision boundary: considering the information comes from two Gaussian dispersions, a simple semi-supervised learning algorithm shall infer a decision boundary that is near to ideal.

4. CLASSIFICATION APPROACHES USING MACHINE LEARNING

Many machine learning approaches are built on the foundation of neural networks. It is the method of categorizing an image into different categories using the labels from the input training dataset. For the problem of picture classification, there are a variety of machine learning methods that shall be grouped into two types: supervised and unsupervised learning methodologies. The studies [12] and [13] both came up with comparable results. The article [14] developed an effective computer-aided diagnostic system using an integration of association guidelines and neural networks. The application of association guidelines minimizes the size of the feature vectors without impacting the overall system's accuracy. They classified images generated after processing the images into normal (non-tumor) and abnormal (tumor) using multinomial multivariate Bayesian references. The authors of [15] have created a system for identifying cancer cells utilizing digital image processing techniques, including feature extrication employing GLCM and categorization utilizing a naïve Bayes method. In their findings, they were able to diagnose lung tumor with an efficiency of 88.57 percent. The research [16] demonstrated an enhanced algorithm for developing support vector machines (SVM) on huge data and issues, as well as how to apply it effectively in SVM. They've also created a strategy for reducing the size of a problem while it's being optimized. A computer-aided diagnosis (CAD) technique for identifying lung tumors early in CT scans and determining whether they are benign or malignant is described in [17]. GLCM was used for feature extraction, and SVM classification was used for classification, as part of the five-phase framework. They utilized a limited dataset of only 25 JPEG photos in their studies, and the findings showed a 96 percent accuracy using the SVM classifier. The study [18] stated the essential characteristics of random forest and stated that it is the extensively utilized algorithm in biological sciences for regression and categorization problems, such as predicting patients' disease states. It also permits extra important knowledge to be extracted from omics data. According to the study [19], a tumor profiling technique depending on tissue microarray information using a random forest clustering strategy. This approach was used to identify and examine kidney tumor that affects adolescents. According to the study [20], a new case-dependent reasoning paradigm for lung tumor subtype diagnosis. To obtain excellent predictive accuracy, they used the gradient boosted regression tree (GBRT) feature selection technique. In the testing, approaches such as k-nearest neighbors (KNN), Naive Bayes classifiers (NB), and SVM were implemented.

4.1. Logistic Regression

For supervised categorization, logistic regression is a robust and common approach [44].An ordinary regression will only model a dichotomous parameter, which often represents whether or not an event occurred. LR helps to determine whether a unique action belongs to a particular category. As it's a possibility, the result shall be between 0 and 1. It is necessary to set a threshold value to distinguish between two categories in order to apply logistic regression as a binary classification method. For instance, if the likelihood value for an input sample is greater than 0.50, it shall be classified as 'class A'; else, it would be categorized as 'class B.' It is possible to use the LR model to model categorical variables with more than two values.

4.2. Naïve Bayes

The Bayes' hypothesis [45] is the fundamental for the Nave Bayes (NB) classification algorithm. This theorem can be used to define the likelihood of an occurrence depending on earlier knowledge of the activity's conditions. Such technique believes that the features in a category are not directly connected to any other characteristics, despite the fact that features in that category may be interdependent [46].

Figure 2 illustrates how the naïve bayes approach operates by assessing the function of categorizing a unique object into either the 'green' or 'orange' category. As there are twice as many 'green' objects as 'orange,' it is logical to suppose that any unique object will have a 'green' membership rather than an 'orange' membership. This belief is referred to as the prior likelihood in Bayesian analysis. As a result, 'orange' and 'green' have prior probability of 0.67 and 0.33, correspondingly. To classify the 'white' item, first draw a circle around it that includes multiple points regardless of the class labels. This diagram considered four points (3 'green' and 1 'orange'). As a result, the probability of 'white' given 'orange' is 0.025 (1÷ 40) and 0.15 (3 ÷ 20) for 'white' given 'green.' Despite the fact that the earlier likelihood represents that the unique 'white' object is more likely to belong to the 'orange' class, the probability indicates that it belongs to the 'green' class. The final classifier in a Bayesian assessment is created by merging both resources of data. To integrate these two types of data, the ‘multiplication' function is utilized, and the result is termed as the 'posterior' likelihood. Lastly, the posterior likelihood of 'white' being 'orange' is 0.017 and 'white' being 'green' is 0.049. As per the NB approach, the unique 'white' object must be categorized as a member of the 'green' category.

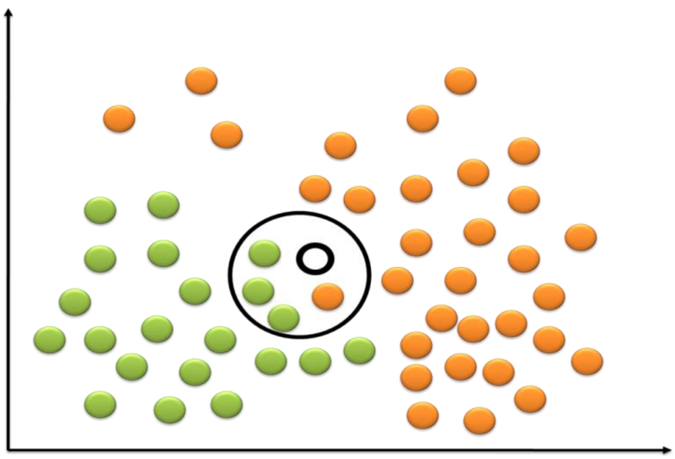

Figure 2. Naïve Bayes illustration. 'White' circle represents a unique sample that must be assigned to the 'green' or 'orange' class.

4.3. K-nearest neighbors

The KNN (K-Nearest Neighbor) method stands out as one of the most essential sample-dependent learning algorithms. The learning process in example-based learning algorithms is dependent on the information in the training dataset. A unique faced sample is classified based on its resemblance to the examples in the training set [34]. The KNN algorithm is one of the simplest and earliest of all classification algorithms[47]. It's like a simple form of an NB classification method. The KNN technique, unlike the NB technique, does not require the utilization of likelihood numbers. In the KNN algorithm, the number of nearest neighbors is taken into account when voting. Diverse classification outcomes can result from different 'K' values for a similar sample object.

4.4. Decision Tree (DT)

Data isolation arrays are used to describe all routes from the root to the leaf node, until a Boolean result is obtained [35]. It is a hierarchical exemplification of nodes and links in knowledge relationships. Nodes indicate purposes when relations are used to classify [36]. The decision tree is a categorization technique with a tree-like topology. Decision Trees are straightforward yet widely used ways for transferring inductive logic into a computer surrounding. It is designed to deal with discretely valued parameters. The primary premise of the inductive philosophy that underpins DT techniques is that a "good" decision tree with learning features must be as short as possible.

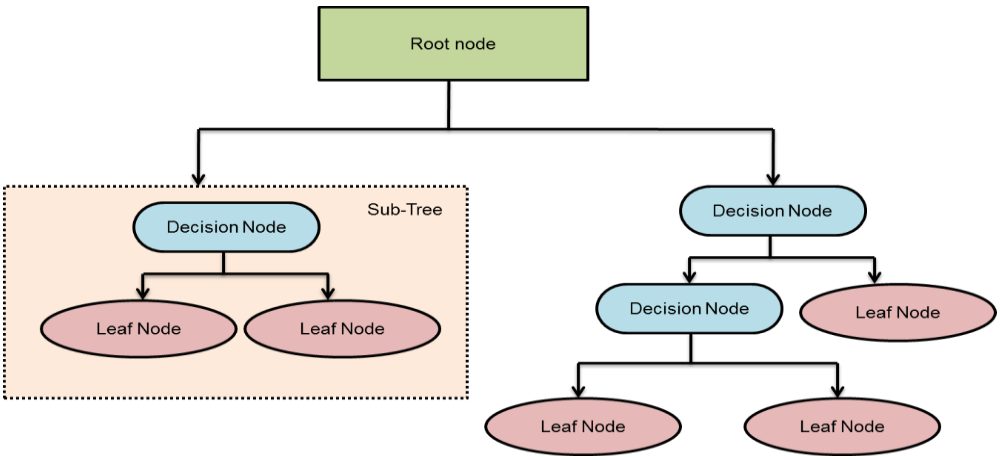

Figure 3. Architecture of Decision Tree (DT)

Decision trees are a strong tool that may be utilized in a variety of domains, including machine learning, processing of images, and recognition of patterns. DT is a sequential framework that effectively and jointly unifies a set of basic assessments where a numerical feature is contrasted to the value of threshold in every assessment [37]. The numeric weights in the neural network of interconnections among nodes are far more difficult to construct than the conceptual rules. DT is primarily used for grouping purposes. Furthermore, in Data Mining, DT is an often-used classification model. Every tree is composed of nodes and branches. Every subset represents a value that the node shall take, and every node indicates features in a class to be categorized. DTs yield a broad variety of utilizations because of their ease of examination and accuracy across many data kinds [38]. Figure 3 depicts a DT example.

4.4.1. Kinds of Decision Tree Algorithms

There are many kinds of decision tree techniques, including Iterative Dichotomies 3, Successor of ID3, Classification and Regression Tree, Chi-squared Automatic Interaction Detector, Multivariate Adaptive Regression Splines, Generalized, Unbiased, Interaction Detection and Estimation, Conditional Inference Trees, Quick, Unbiased and Efficient Stat (QUEST). An overview of the most commonly used decision tree algorithms is presented in Table I [39].

Table 1. Comparative analysis of frequently employed DT techniques

Techniques	**Classification and Regression Tree**	**Successor of Iterative Dichotomies 3**	**Chi-squared Automatic Interaction Detector**	**QUEST**
The metric employed to collect input variables	Gini index,Twoingstandard	Entropy info-gain	Chi-Square	J-way ANOVA for continual or ordinal parameters, Chi-square for categorical parameters
Pruning	Applying a single-pass method for pre-pruning	Pre-pruning using a single-pass technique	An independent pre-pruning strategy based on Chi-square tests	Post-Pruning
Dependent Parameter	Continuum or categorical	Continuum or categorical	Categorical	Categorical
Input Parameters	Continuum or categorical	Continuum or categorical	Continuum or categorical	Continuum or categorical
Nodes are divided at every node	Binary; Divided on linear integrations.	Multiplex	Multiplex	Binary; based on linear integrations

4.4.2. Entropy and Information Gain

The impurity or randomness of a dataset is measured using entropy [40]. The entropy value is always between zero and one. Its number is finer whenever it equals zero, and it is worst whenever it equals zero, that is the nearer it is to 0, the better. The entropy of categorizing set E with respect to the c states[41] if the target is G with varying attribute numbers. "Equation (1)" demonstrates this.

$$Entropy(E) = \sum_{i=1}^{c} S_i \log 2^{S_i} \tag{1}$$

The sample count is denoted by the proportion of the subset and the i-th feature number by the number of features in the subset.

Mutual information is a statistic for segmentation that is often referred to as information gain. This tells you how much you know about the value of a random variable. It's the polar opposite of entropy, with a greater number indicating finer performance. Information gain can be defined using Equation (2), as indicated in the definition of entropy.

$$Gain(E, A) = \sum_{\Sigma v \in V(A)} \frac{|E_v|}{|E|} Entropy(E_v) \tag{2}$$

Here the range of feature$A$ is (A), and E_v is a subset of set Esimilar to the feature number of feature$v$.

4.4.3. Advantages and disadvantages of DT

The decision tree technique is a supervised learning method whose main goal is to develop a training framework, which shall be utilized to forecast the category or value of target parameters using decision guidelines learned from the training information. The decision tree algorithm shall be employed to handle regression and categorization issues, although it has several advantages and disadvantages [42, 43], as shown in Table 2.

Table 2. Benefits and Drawbacks of DT

Benefits	**Drawbacks**
Simply to comprehend.	It is possible to thwart the best decision-making system.
Quickly transformed into a set of manufacturing principles.	The decision tree has a lot of layers that renders it intriguing.
Can categorize both numeric and categorical results, and yet only categorical attributes could be created.	The decision tree's computation intricacy can rise as additional training samples are added.
No a prior hypotheses are used when evaluating the quality of the outcomes.	Incorrect decisions can follow.

4.5. Support Vector Machines (SVM)

SVM is a famous discriminant approach and a robust classification framework in machine learning [25]. It has superior generalization ability than other data mining classification methods [26, 27]. It also contains a collection of improved theoretical approaches for dealing with nonlinear detachable data. The focus of this strategy is to define a line with the maximum total distances from nearby points in order to isolate situations that are linearly separable; for linear inseparable conditions, the kernel functionality is required [28].Support vector machine is mostly used in two scenarios. Linearly detachable information is the first class, while linearly inseparable information is the second [29, 30]. The kernel method is employed to translate information from lower-dimensional region to higher-dimensional region for linearly separable information, and then relaxation variables are employed to make the data linearly separable.
The equation of the binary categorization discriminant operation is represented by:

$$h(a) = u^P a + y \tag{3}$$

Then, $h(a) = 0$, denotes hyperplane H that is employed to isolate the two kinds of instances, and the categorization guidelines are as in equation (4):

$$b_i(u^P a_i + y) \geq 1 \tag{4}$$

In the SVM classification issue, every mathematical operations are stated as inner products. To complete the relevant feature mapping, replace internal product methods with kernel functions [33]. At the moment, there are three basic types of kernel functions, with the following formula:

$$K_{play}(a, a_i) = [(a, a_i) + 1]^q \tag{5}$$

Using polynomial classification, a q-dimensional classification is produced.

Radial basis kernel function (RBF):

$$K_{ebf}(a, a_i) = exp\left(-\frac{|a-a_i|^2}{\sigma^2}\right) \tag{6}$$

Sigmoid kernel function:

$$K(a, a_i) = \tan h\,(v(a.a_i) + z) \tag{7}$$

Different kernel functions must be selected depending on the problem [31]. Because of their outstanding classification capabilities, RBF and polynomial kernel functions are commonly utilized [32]. At the same time, the classification effect is determined by the choice of each SVM parameter value.

Kernel function is essentially a two-dimensional to multi-dimensional mapping. It would become linearly detachable whenever linear indivisibility is converted to multiple dimensions using a kernel function, that implies it could be divided utilizing technique one. Information that is linearly embedded in the system could be linearly detached at this point. To calculate the interior product of two vectors in a higher-dimensional area, the kernel function is used. Mercer's condition must be met for it to be approved for use as the kernel function.

The comparison table for the merits and demerits of different machine learning algorithms used for image classification is provided in table 3. Fugure 4 represents the accuracy for machine learning approaches.

Table 3. Machine learning approaches for image classification with their advantages and disadvantages

Classification approaches	**Advantages**	**Disadvantages**
SVM[27]	➢ Better accuracy ➢ Easily handles complex non-linear data points	➢ In massive data, it's challenging to use. ➢ Execution is comparatively slower
k-NN[27]	➢ It is simple to execute. ➢ Training is completed more quickly.	➢ It necessitates a lot of storage space. ➢ Knowledge representation has a low level of transparency.
Decision Tree[39]	➢ The development of decision trees does not necessitate domain expertise. ➢ It has simple meanings and can manage numerical and categorical data.	➢ It's an unreliable classifier. ➢ Categorical output is produced.
Logistic Regression[48]	➢ It is simple to design and train ➢ Shall manage nonlinear and interaction effects	➢ It is impossible to forecast continual results. ➢ Over fitting ➢ To acquire consistent results, a high sample size is required
Naïve Bayes[48]	➢ Simple and easier to implement ➢ More precision due to the increased probability value	➢ Loss of accuracy ➢ Substantial presumption about the data distribution's structure

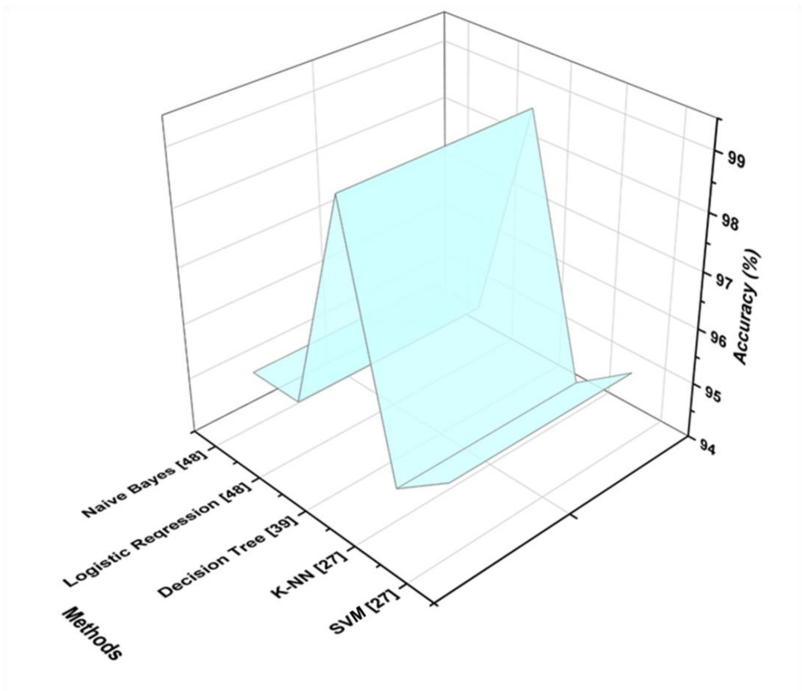

Figure 4. Accuracy for machine learning approaches

5. IMAGE FEATURES FOR DETECTING CANCER

Generally, benign cancerous cells are round-shaped or elliptical, with smooth borders, fine chromatin, abundant cytoplasm, and homogeneous distribution. Malignant cancerous cells have irregular forms with rough or spiky margins rather than smooth ones. A malignant nucleus has a volume that is typically one to four times that of a normal nucleus. Different features of cancer images are useful for differentiating the cancer cells from healthy cells as well as for distinguishing malignant tumors from benign tumors. The important image features such as spatial, morphological, and texture features for image classification are explained as follows.

5.1. Morphological features

Morphological features include the tumor area, tumor perimeter, tumor compactness, major and minor elliptical axes, tumor curvature, sphericity, tumor radius and diameter, and tumor boundary [49]. Only discrete nuclei are used to calculate the area and perimeter. When determining tissue type, the size and form of the structures present within a group of glands are crucial. Tumor area identification allows for the assessment of tumor size and shape. The impact of tumor shape on cancer prediction has also been examined. The size of tumor size is an important factor for cancer prognosis. As a result, characteristics based on tumor shape and the border is retrieved. The rough tumor border has been identified as a sign of a malignant tumor in X-Ray and CT imaging investigations. As a result, tumor region borders must be properly defined for the efficient differentiation of cancerous cells [50]. Different bacterial for cell morphological illustrated in Figure 5. Here A. Gonococcus is negative coccus bacteria, B. Streptococcus is positive coccus bacteria, C. Staphylococcus is positive coccus bacteria, D. Escherichia coliis rod shaped bacteria, E. Treponema pallidum is spiral shaped bacteria, F. Helicobacter pylori its is spiral shaped bacteria, G. Vibrio

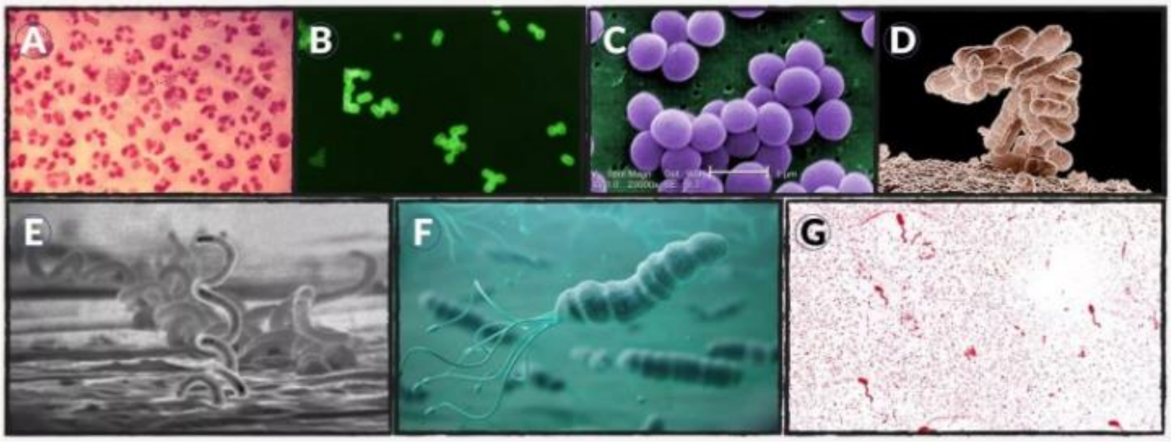

Figure 5. Different bacterial for cell morphological

5.2. Spatial Features

Spatial interactions among neighboring cells in the tumor region are investigated by which super-cells are formed by fusing the closely interacting cells. Combine the super-cells at the gland level to identify the cellular and nuclear community. This data from the community aids in the extraction of characteristics for diagnostic purposes. The spatial distribution of tumor cells in benign and malignant pictures differs. Hence, these features can be employed for cancer classification. Based on spatial relationships existing between tumor cells, nuclei, and gland, specific features such as the number of distinct nuclei layers surrounding the gland and lumen, standard deviation (SD), average, minimum, and a maximum of nuclear perimeters and areas, different ratios like lumen area to the tumor area, tumor area to the perimeter, and nuclei perimeter to tumor perimeter can be extracted. The Delaunay diagram, Voronoi diagram, and minimum spanning forest (MSF) are some of the techniques utilized to collect the spatial attributes [51] A overview of spatial feature analysis shown in Figure 6.

5.3. Voronoi diagram

All locations in the Euclidean plane of the image containing the finite number of distinct points are connected with the nearest member of the set of points based on the Euclidean distance. The Voronoi diagram is drawn using the centroids of the linked areas. It consists of a set of polygons. Area, Perimeter, chord length, minimum to maximum ratio, and roundness factor of polygons are different Voronoi features. [52] Used Voronoi diagram for extracting spatial features of lymphoid neoplasms.

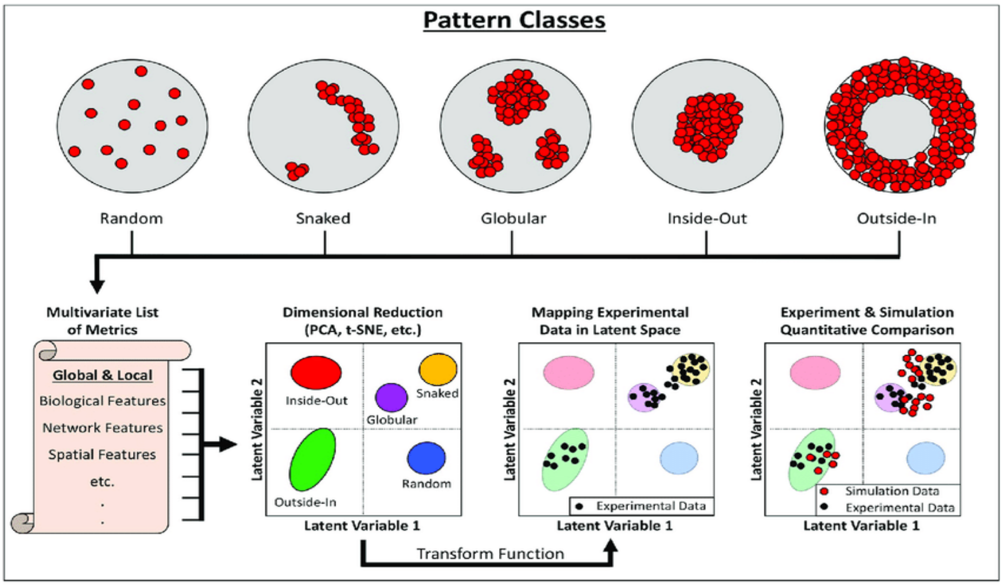

Figure 6. Spatial Feature analysis outcomes

5.4. Delaunay Diagram

If the adjacent cells share an edge, a straight line connects two nodes in a planar Voronoi network. The Delaunay graph is made up of all these lines. To acquire the spatial characteristics, the average, SD, minimum, and maximum of areas, perimeters, and side lengths of each Delaunay triangle are determined [53].

5.5. Minimum Spanning Forest

The minimum spanning tree (MST) is created by utilizing the edge weight which is obtained based on the distance existing between the nodes in the tumor picture. The MSF is made up of several MSTs. In the MSF, the time, SD, average, minimum, and maximum length of sides is computed. The MSF is recommended since it can determine the image's pixel distribution using intensity characteristics. Malignant tissues have unique qualities in that they occupy the maximal density in the smallest amount of space [54].

5.6. Texture Features

Interpreting tumor picture texture, which provides details about the scanned structures, may help distinguish cancerous from normal cells. The texture features include energy, correlation, entropy, Haralick correlation, inertia, cluster prominence and shade, inverse difference moment, average intensity difference (AID) existing between outer and inner bands surrounding the boundary of tumors, AID between pixels of the whole tumor, and 25 percentage brighter pixels, AID between tumor and surrounding tissues, AID between tumor and region behind tumors, AID between region present behind the tumor and surrounding tissues [55]. Grey-level co-occurrence matrix (GLCM), Speeded Up Robust Features (SURF), and Scale Invariant Feature Transform (SIFT) are some of the useful techniques available for representing the changes in the texture of the tissues and nuclei present in the tumor regions. The texture-based feature extraction is shown in figure 7.

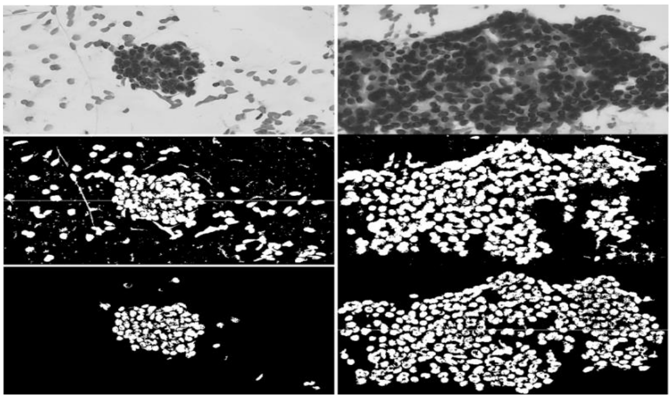

Figure 7.Texture based Feature extraction

5.7. Grey-Level Co-occurrence Matrix

For processing gray-level tumor images, the GLCM model was employed. When using GLCM functions on an image, calculate the frequency with which pixels with certain values and spatial connections exist in the picture, construct a GLCM, and produce statistical data from this matrix. For the classification of cancerous cells from normal cells, GLCM characteristics namely energy, contrast, entropy, correlation, and homogeneity may be retrieved. Correlation implies the linear reliance on nearby pixels, whereas contrast signifies the existence of noise, edges, and wrinkled textures. According to figure 8, uniformity, orderliness, and entropy are measured as the extent of disorder among pixels, while homogeneity indicates smoothness of the gray level pattern [56].

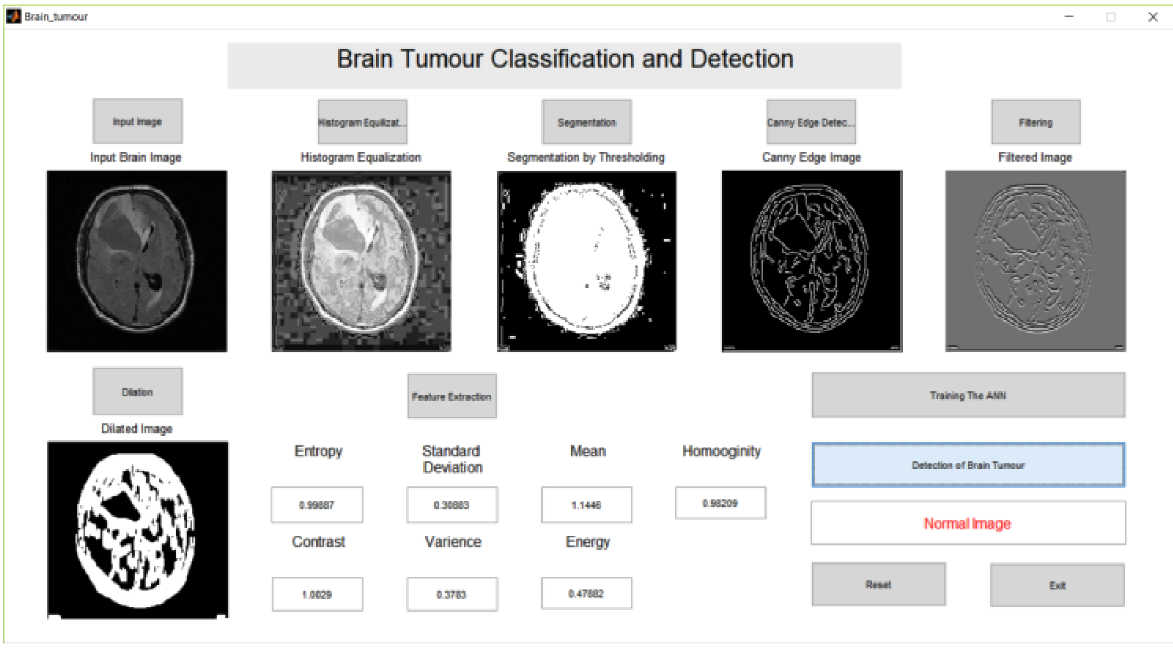

Figure 8. GLCM method feature extraction

5.8. Speeded Up Robust Features

In aspects of distinctiveness, repeatability, speed, and robustness, SURF significantly outperformed other descriptors. Detection of interest points, description of interest points, and matching of feature descriptors are the three phases of SURF [58]. It is a powerful detection and description approach for local features that comprises the development of feature descriptors, the building of a scale space and Hessian matrix, the position of feature points, and the assignment of the primary direction of feature points. The SURF algorithm is built around the Hessian matrix. A square area around the feature point is routinely divided into smaller sub-regions along the main direction. A four-dimensional descriptor vector is present in each sub-region, which represents the total vertical and horizontal responses, as well as the total of the absolute values of vertical and horizontal responses, resulting in a variety of texture characteristics.

5.9. Scale Invariant Feature Transform

SIFT is known as a volumetric feature because it uses key points to determine the edges of an image. SIFT characteristics are used because they are resistant to tiny changes in light, size, picture rotation, and perspective. Localization of key points, Scale-Space Peak Selection (SSPK), Assignment of orientation, computation of keypoint descriptor, and matching of keypoint are the five basic phases of the SIFT method. SSPK was utilized in the first step to create a Gaussian Pyramid (GP) [58]. To compare image features for cancer diagnosis, see table 4.

Table 4. Comparison of image features for cancer diagnosis

S.no	Reference and methods	Title	Merits	Demerits
1.	[59] Morphological features	Classification of human stomach cancer using morphological feature analysis from optical coherence tomography images	Over 95% accuracy was shown by the best feature across all five classifiers.	The bottom low-intensity zone is due to the technique's limited ability to penetrate tissues. Consequently, not much was known about these numbers.
2.	[60] Spatial Features	Convolutional neural networks in skin cancer detection using spatial and spectral domain	More data are required, and the acquisition of training data must be organized, in order to create a more broad and dependable model.	The limited data set is the primary drawback of the research. Although so we had access to over 100 million images, we ultimately only found 61 distinct malignancies. The ground truth labelling is predicated on a diagnostic evaluation of the entire lesion, which is another constraint. A lesion has a good chance of encompassing many classes.
3.	[61] Voronoi diagram	Breast cancer classification in pathological images based on hybrid features	since it has highly distinctive visual qualities.	Whatever the designation, it's difficult to overlook the pattern right away.
4.	[61] Delaunay Diagram	Breast cancer classification in pathological images based on hybrid features	Delaunay triangulations are widely used to build meshes for space-discretized algorithms such as the finite element technique and the finite volume approach of physics modeling.	Delaunay diagrams are used less often to extract the spatial characteristics because of their complexity.
5.	[61] Minimum Spanning Forest	Breast cancer classification in pathological images based on hybrid features	Networks employ spanning tree protocol to avoid broadcast storms. This provides redundancy to prevent spanning tree or network loops.	When a new spanning tree or network spanning tree is constructed, spanning trees automatically recalculate, although this might cause a network outage.
6.	[62] Texture Features	Transition Zone Prostate Cancer: Logistic Regression and Machine-Learning Models of Quantitative ADC, Shape and Texture Features Are Highly Accurate for Diagnosis	For prior research employing any novelty has indicated that textural features are essential for cancer diagnosis.	Texture features cannot even distinguish TZ tumours from normal Prostatic lesions inner diameter.

7.	[63] Grey-Level Co-occurrence Matrix	Analysis of breast cancer using grey level co-occurrence matrix and random forest classifier	Some texture measures, including as correlation, contrast, energy, and homogeneity, have been proposed for benign-malignant mass classification; however, these features only quantify the association between adjacent pixels and fail to reflect structural similarities within nearby areas.	The accurate mass categorization of masses is essential for it too.
8.	[64] Speeded Up Robust Features	Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification	For local, similarity-invariant representation and comparison of pictures, the Speeded Up Robust Features is a quick and robust approach.	Interest points of a given lower-quality picture are specified as prominent features from a scale-invariant representation, as is the case with many other local descriptor-based techniques.
9.	[65, 66, 67, 68, 69] Scale Invariant Feature Transform	Computer aided classification of neuroblastoma histological images using scale invariant feature transform with feature encoding, the presence of noise in an image is inevitable	While the specificity of Scale Invariant Feature Transform (SIFT) has been found to improve upon the specificity of visual analysis by a pathologist, the experimental results suggest that combination of (SIFT) with the bag of characteristics is a potential technique for categorization of neuroblastoma histological images.	The detection of cancer using this method is poor.

6. CONCLUSION

Machine learning algorithms are increasingly being employed in a variety of areas. Using such methods to enhance sustainability initiatives in image analysis for detection of cancer could be beneficial. In machine learning, there are two kinds: unsupervised and supervised. We use supervised learning when there is a limited amount of information and clearly labeled dataset for training. For big datasets, unsupervised learning will provide greater performance outcomes. This study examines a number of machine learning techniques. Nowadays, everyone, intentionally or unintentionally, employs machine learning. Especially, in the biomedical field, for the classification of images in cancer detection, machine learning algorithms are employed. This paper provided a systematic review on five different machine learning algorithms used for classification purposes. The merits and demerits are compared for all the methods discussed.

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