Enhanced Colon Cancer Prediction Using Capsule Networks and Autoencoder-Based Feature Selection in Histopathological Images

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***Abstract*—The malignant development of cells in the colon or rectum is known as colon cancer, and because of its high incidence and possibility for death, it is a serious health problem. Because the disease frequently advances without symptoms in its early stages, early identification is essential. Improved survival rates and more successful therapy depend on an early and accurate diagnosis. The reliability of early detection can be impacted by problems with traditional diagnostic procedures, such as high false-positive rates, insufficient sensitivity, and inconsistent outcomes. This unique approach to colon cancer diagnosis uses autoencoder-based feature selection, capsule networks (CapsNets), and histopathology images to overcome these problems. CapsNets capture spatial hierarchies in visual input, improving pattern identification and classification accuracy. When employed for feature extraction, autoencoders reduce dimensionality, highlight important features, and eliminate noise, all of which enhance model performance. The suggested approach produced remarkable outcomes, with a 99.2% accuracy rate. The model's strong capacity to detect cancerous lesions with few mistakes is demonstrated by its high accuracy in differentiating between malignant and non-malignant tissues. This study represents a substantial development in cancer detection technology by merging autoencoders with Capsule Networks, so overcoming the shortcomings of existing approaches and offering a more dependable tool for early diagnosis. This method may improve patient outcomes, provide more individualized treatment regimens, and boost diagnostic accuracy.**

***Keywords*—Colon cancer prediction; capsule network; autoencoder; histopathological images; early cancer detection**

I. Introduction

Colon cancer is one of the common cancers globally, and also has its contribution to the cancer related deaths. Cancer of the colon is generally said to start out as small growths in the outer lining of the colon or rectum and may progress to become malignant tumors [1]. In case this condition is not diagnosed early enough and management commenced, it can develop silently and hence make the treatment process more challenging. One cannot overemphasize on the need to have colon cancer detected early. Colon cancer is relatively easy to cure and very treatable if it is detected in its preliminary stage. It is possible to detect and remove precancerous polyps and stage I malignancies with colonoscopy and other screening methods before the manifestation of symptoms. As a result, common people besides those who are over 45 years or those with the history of this complaint must opt for these tests more often. The implication of colon cancer extends to the families, the communities and the health systems over the directly affected individual. There is need to give early diagnosis and treatment since the condition leads to severe physical, emotional, and financial complications [2]. Improving possibilities for early detection of diseases and tailoring programs for patients require new discoveries in the field of medicine, for example, development of advanced techniques to visualize body conditions or new types of computational models for prognosis. Colon cancer can be anticipated employ modern methods and equipment in identifying the disease before it spreads hence improving the prospects of the ailment. Modern methodologies of prediction use numerous devices, including genetic tests, imaging, and ML algorithms. For instance, in Histopathological image analysis, the precise patterns in tissue samples may be seen by employing CapsNets in which the changes in size might mean malignant alterations. Additionally, using diversified data gathered from various sources, involving the lifestyle factors of the patient, his family history, and demographics, predictive models can be created that would assess the risk level of the given individual.

Possibly, there is a way to enhance these predictions as such methods as feature selection and dimensionality reduction with the help of autoencoders could focus on the most relevant characteristics [3].

The advancements demonstrate how sophisticated prediction approaches and individualized care may dramatically enhance early diagnosis and treatment, improving patient outcomes and streamlining healthcare processes. An important step forward in colon cancer treatment and early diagnosis is the machine learning-based prediction model that has been suggested [4]. It means that, with the help of applied ML algorithms, the scholars will look for various tendencies and the potentially linked risks associated with colon cancer, utilizing huge datasets of histopathologic data, genetic features, or patients' characteristics. Popular DL methods CNN and CapsNets are applied in the process of examining medical images to identify the signs that might suggest the presence of malignant tumors. To increase the model performance, it is also possible to apply the ML model to use multiple modalities as image findings, tests and patients' history. These models may be further refined into feature selection methods such as autoencoders to identify the pertinent data features for prediction [5]. Since these complex advancements of modern day's ML categorically predict individual responses towards various drugs, they not only enhance early diagnosis, but also facilitate development of composite patient-centered regimes. The capability of these models to predict has been on the rise and more so depending on the large and diverse information that has been fed to them perhaps yielding into better and faster response [6]. In general, the idea to integrate ML into the prediction of colon cancer can be considered as rather perspective in terms of reducing mortality rates as well as improving patients' quality of lives due to precise diagnosis.

The novel neural network design technique known as CapsNets addresses the limitations of the original CNN in terms of recognizing spatial hierarchies and connections. The constraints of CNNs in preserving the relative position and orientation of input are overcome in CapsNets by capsules, which are collections of neurons cooperating to identify certain patterns and their spatial correlations. Proprietary routing methods amongst capsules provide precise data transfer over the network. The main breakthrough is that features' presence and posture are captured by capsules, which improves the network's comprehension of intricate spatial data [7]. This hierarchical method certainly supports the idea of adjusting the CapsNets based on the changes in the object orientation, along with their ability to generalize from very little training data. In such problems as image identification and segmentation, where feature localization is critical, CapsNets are very effective because they enhance the network's ability and capacity and modeling complex spatial relations. It is an optimal method for applications requiring complex pattern recognition as they do not degrade the feature in various views and transformations. Among neural networks designed for unsupervised learning, the proper name is autoencoders. It provides mainly the aspect of learning the best representations through the encoding and decoding processes. A low dimensional representation of input data is mapped by an encoder network into an autoencoder, and the low dimensional representation is mapped by a decoder network into the original data to reconstruct it. It is useful for finding and retrieving the characteristics of the data while filtering out the outliers and the redundancies. Autoencoders are used in denoising of data, feature extraction, and dimensionality reduction. Other extensions are variational autoencoder which can model complex distributions of the data or sparse autoencoder which forces the latent space to be sparse.

Enhancing the accuracy and efficiency of the consequent image processing, two special models, namely CapsNets and autoencoders, are indisputably effective for identifying colon cancer. Spatial hierarchies were managed well and fine details in the histopathology images were recognized by CapsNets thus improving the detection of weak malignant features. On the other hand, autoencoders are useful in feature learning and feature reduction in which it down samples the important features of the images and reduces on the noises. Such integration is important to assist researchers in developing strong models for assessing medical images on the basis of time efficiency, which in this case, can lead to enhanced patient results due to better early diagnosis of colon cancer. Key contributions of the proposed work are:

1) Demonstrates increased detection accuracy for colon cancer by utilizing CapsNets' capacity to identify intricate spatial correlations, as opposed to more conventional image processing techniques.

2) Provides use of autoencoders to efficiently reduce dimensionality and extract features, producing input for the capsule network that is more insightful and pertinent.

3) Exhibits resilience in model performance over a range of datasets and imaging settings, improving the approach's generalizability.

4) Lowers false positives and false negatives in the detection of cancer, enhancing the precision and dependability of the diagnosis.

5) Permits for the customization of therapeutic and diagnostic approaches by combining patient-specific data with model predictions.

The suggested study starts with an overview of colon cancer and the urgent need for better diagnostic approaches because of the shortcomings of current practices in Section I. The Related work is reviewed in Section II, which also highlights the difficulties in early identification of the current approaches. The problem statement is described in Section III. The procedure for gathering data, the pre-processing measures, and the use of CapsNets for pattern detection and feature extraction are all covered in Section IV. The performance measures are presented in Section V and ending with the Section VI, Future work and conclusion.

II. Related Works

Ali and Ali [8] utilizes two forms of Convolutional Layers Block, the first of which is the CLB while the second one is the SCLB enhanced through an advanced computerized system to enhance the capability of identifying the lung and colon cancer. Histopathological images are processed with the help of a multi-input capsule network in this system. To undo colour distortions applied by the microscope during the preparation of histopathology slides, the SCLB undergoes the images enhanced

with multi-scale fusion, colour correction function, gamma correction, and image enhancement items. The CLB deals with raw photos in the meantime. This multi-input method certainly outlines a huge improvement as to the feature learning of the model. It turned out that when using the LC25000 dataset, the work of the model was commendable in terms of the result accuracy obtained in the diagnosis of lung and colon pathologies. The study has many limitations, however, mainly due to the fact that its source data were limited by the range of LC25000 and could not exactly reflect the characteristics of actual clinical data. This could be an effect on the model's robustness and transferability across different patient populations and histological differences.

Ahmed [9] learned about Artificial Neural Networks (ANNs), which are powerful nonlinear regression techniques have been used in colon cancer survival and classification for more than 45 years. This paper introduces fundamentals of three-layer feedforward ANN with backpropagation, which are used in cancer studies. MAS and colon cancer. In the cases where ANNs were employed in lieu of such statistical or clinicopathological approaches, there has been an overall enhancement of colon cancer classification, and survival prognosis as stated in the following discussions of the literature. Nevertheless, different types of ANNs used in biochemical research have some specific prerequisites in design and reporting to ensure the quality and credibility of obtained data. Nonetheless, the study is limited by the need for large, high-quality datasets and the possibility of over-learning, which could impact the models' generalisability across patient populations and care settings.

Kavitha et al. [10] learned about the automated processes that are essential in identifying Colorectal cancer; especially through endoscopic and histological images. This is important in as much as the enhancement of, clinical decision making and reduction of effort. Modern DL methods are workable in the detection of polyps on images and motion images, and segmentation of the latter. Image patches and CNN integration as well as the pre-processing technique are among the primary AI techniques deployed in the majority of the modern diagnostic colonoscopy stations for invasive malignancy approximation. Features like transfer learning have detached the user from the process and made even small sets yield great results hence highly accurate. Explainable deep networks that offer transparency, interpretability, consistency, and equality in the provision of healthcare are still available despite all the developments. This paper describes the recent advancements in such models and highlights the research limitations when developing technology for the prediction of colorectal cancer. However, there are still some limitations For example, one needs to have vast and diverse amount of data, and non-restrictive protocols to ensure that the model can generalize across diverse patient cases and populations.

Tasnim et al. [11] analysed that advancement in medical and Health care diagnosing has been brought about through advancement ion computer technology. Mentioning that cancer occupies the second place among all causes of death in the world, early detection is crucial for the rate of survival, especially colon cancer, which, despite its relatively high incidence and lethality, is more accessible. This paper focuses on the exploration of CNN with the imaging data of colon cells with the objective of automating cancer detection. The CNN with max pooling layers, average pooling layers, and MobileNetV2 are used in this study. The models with max pooling and average pooling achieve the accuracies of 97. 49% and 95. ResNet and MobileNet achieve mean accuracy of 48%, and 52% respectively, on the other hand MobileNetV2 achieves highest accuracy with 1 % data loss rate. 24%. While the aforementioned outcomes seem promising, the present study is still limited in several ways: the demand for large and high-quality datasets and the challenge of ensuring model robustness across different patients' groups and clinical scenarios.

Babu and Nair [12] investigated an automated detection of colon cancer using histological images which is significant for the highest possible outcome in the treatment. Traditional methods are based on low level features that are selected manually and it might not be accurate. Overall, for this problem, both supervised as well as unsupervised DCNN were applied for assessing of colon cancer histopathology images. Many of the photometric results were rotated and flipped to eliminate class disparity. From the result of the experiments the analyst was able to compare with the previous approach and found that the supervised models such as Inception were able to classify the colon cancer histopathology images with higher accuracy. Yet, a similar autoencoder network was built to extract and cluster the features from these images and to introduce the better clustering ability of the improved autoencoder network for the previously used unsupervised image processing network. Despite these advances, the study still has limitations such as the need for greater big and diverse datasets and the technical challenge of achieving model robustness and transferability across different clinical scenarios.

Schiele et al. [13] presents the Binary ImaGe Colon Metastasis classifier (BIg-CoMet), developed from the InceptionResNetV2 architecture, and operates on histologic images to partition colon cancer patients according to distant metastatic risk. Images of tumor sections stained with cytokeratin were used to train the model, along with image augmentation and dropout, to prevent overfitting. The former was investigated in a validation cohort consisting of 128 patients with BIg-CoMet showing an AUC of 0. 842, thus showing acceptable ability to distinguish between those with the metastases and those without. A marked distinction in the KM plots associated with metastasis-free survival also strongly supports the conclusion that the high-risk subjects, as defined by BIg-CoMet, have a much graver prognosis than do the other patients. This new risk variable portrayed a greater ability to perform as compared to other models with its positive predictive value standing at 80%. It depicted good results for both the subgroups of UICC and particularly for UICC III. As proven in this work, the proposed BIg-CoMet can efficiently sort out MCI or colon cancer patients based on the photographs of tumor architecture. However, the study still has its limitations in that the experiment needs to work with larger and more diverse datasets, and the inherent problem of how to ensure the stability and transferability of the model in different clinical scenarios.

Talukder et al. [14] Suggested a study of a composite feature extraction model for the classification of Lung and colon cancer. Combining deep feature extraction, ensemble learning, and

high-performance filtration techniques, it improves cancer diagnosis. It presented accuracy rates for colon cancer at 100 per cent and for rectal cancer at 99. that for the both cancers were 30 percent, and 99 percent, respectively. The performance was found to be 05% for lung cancer when tested on the LC25000 histopathology datasets. These findings indicate the higher efficiency of the suggested hybrid model compared to the existing approaches, which raises a possibility of its practical application in cancer diagnosis. The study must be validated to ensure the model is not limited to the specific cohort used or specific clinical scenarios.

CNN and hybrid ensemble approaches are examples of the sophisticated cancer detection models that have been created recently and have shown excellent accuracy in detecting lung and colon cancers. Through enhanced feature extraction and image variance management, these models overcome the drawbacks of conventional techniques. They frequently, however, rely on particular datasets, which raises questions over their generalizability across various clinical contexts and patient demographics. In order to address these drawbacks, the suggested approach combines deep learning, multi-scale fusion, and hybrid ensemble feature extraction, with the goal of improving resilience and practicality in real-world clinical settings through the use of diverse and sizable datasets for validation.

Current colon cancer detection techniques are hindered by high false-positive rates, low sensitivity, and variable results, hindering early diagnosis. Conventional CNN-based models are not good at extracting spatial hierarchies in histopathological images and tend to miss important malignant features. Feature selection methods currently used are not effective in reducing dimensionality, resulting in redundant information and computational inefficiencies. Most diagnostic methods that are available are costly, time-consuming, and need specialized skills, making them inaccessible. This research fills these gaps by combining Capsule Networks (CapsNets) with autoencoder-based feature selection, guaranteeing enhanced feature extraction, spatial hierarchy retention, and improved classification accuracy, thus providing a more accurate and economical early detection system.

III. Problem Statement

Cancer continues to be the second greatest cause of death globally, despite significant advancements in science and healthcare over the previous forty years. More over 25% of cases are lung and colon cancers, making them among the deadliest and most common tumors. Even while early diagnosis is stressed as a crucial tactic for raising survival rates, the techniques used today are frequently expensive and time-consuming [15]. There is a desperate need for the development of an automated, precise, as well as economical method to aid in the early detection as well as classification of tissue originating from lung or colon cancer. Consequently, the proposed study aims at alleviating such deficiencies in the prediction of colon cancer through autoencoder-based feature selection and CapSNets. Thus, maintaining spatial hierarchies and detecting detailed patterns, CapsNets enhance the potential of the network to identify the malignant feature that standard CNNs would ignore. The proposed project will try to increase the efficiency of colon cancer detection by the initial preprocessing of data containing autoencoders along with the decrease in the dimensions and extraction of critical features. Such an integration approach will ensure that early detection is more accurate than it is now and; therefore, the outcomes as well as the kind of treatment a patient receives in the future will be well determined.

IV. Enhanced Colon Cancer Prediction Using CapsNets and Autoencoder-Based Feature Selection

Colon cancer is quite prevalent and can be devastating, which emphasizes the significance of early identification and precise diagnosis. Since the condition is generally asymptomatic in its early stages, early detection greatly boosts the odds of effective therapy. Early detection of colon cancer depends on advanced diagnostic models and preventive screening. Efficiently evaluating complicated histopathological images, machine learning techniques like autoencoders and CapsNets might improve the accuracy of colon cancer detection. Permitting early and accurate forecasts, these cutting-edge procedures not only increase survival rates but also lessen the psychological and physical toll on patients and their families. Furthermore, it allows early and tailored therapy to be administered, maybe one that could avoid the disease from moving to more advanced stages. Thus, incorporating such advanced technologies into the system of delivering health care, it might be possible to reduce the costs of medical treatments and improve the quality of the patients' lives due to more efficient and preventive measures. Through analyzing and identifying early signs and risk factors of colon cancer, it is possible to develop creative strategies to predict and treat it, thus stressing the importance of progress in the sphere of technology concerning health care and social security.

Fig. 1 shows a methodical procedure for utilizing histopathology scans to identify lung and colon cancer. The first step of the procedure is Data Collection, during which histological images of colon and lung cancer are acquired. Data pre-processing, which entails improving the quality of the images for analysis by shrinking, normalizing, and reducing noise, comes next. The following stage is called Feature Extraction using Auto-Encoder, in which autoencoders are used to reduce dimensionality and concentrate on important patterns while identifying and extracting the most pertinent features from the pre-processed images. After that, a Capsule Network for Model Deployment is used with these extracted characteristics, taking use of the network's capacity to maintain spatial hierarchies and precisely identify intricate patterns. Ultimately, Performance Evaluation is used to evaluate the model's efficacy and make sure that the predicted accuracy and reliability fulfill the required criteria, which in turn helps with cancer early detection and diagnosis.

A. Data Collection

The Lung and Colon Cancer Histopathological Images collection is used to create and assess cancer detection algorithms as a benchmark and as a review tool. Twenty-five thousand histological photographs, divided into five categories of lung and colon tissue, are included in it. With their 768 by 768 size, these images are perfect for creating machine learning applications. The first dataset comprises 750 verified and

HIPAA-compliant photos, comprising 250 samples of benign lung tissue, 250 samples of lung adenocarcinoma, and 250 samples of lung squamous cell carcinoma. Further, five hundred samples of colon tissue were taken, for which two fifty samples of benign colon tissue were collected and two fifty samples of colon adenocarcinomas were also collected. A new set of 25,000 photos was augmented with the help of the Augmentor program that introduced rotations, flips, zooms, etc., into photos in order to mimic variability and increase the robustness of the prediction models. This was done in a bid make the dataset more interpretable and more diverse. Due to increased augmentation and better resolution of this dataset, it is highly recommended for training and validation of ML models which employ complex approach like Autoencoders and CapsNets. Using this information, the specialists can enhance the performance of methods for cancer identification, hence enhancing the health of patients. The given dataset of lung and colon cancer samples is valuable in the further work on using IT in the fight against cancer due to its well-annotated test examples and the presence of samples of both benign and malignant tumors [16].

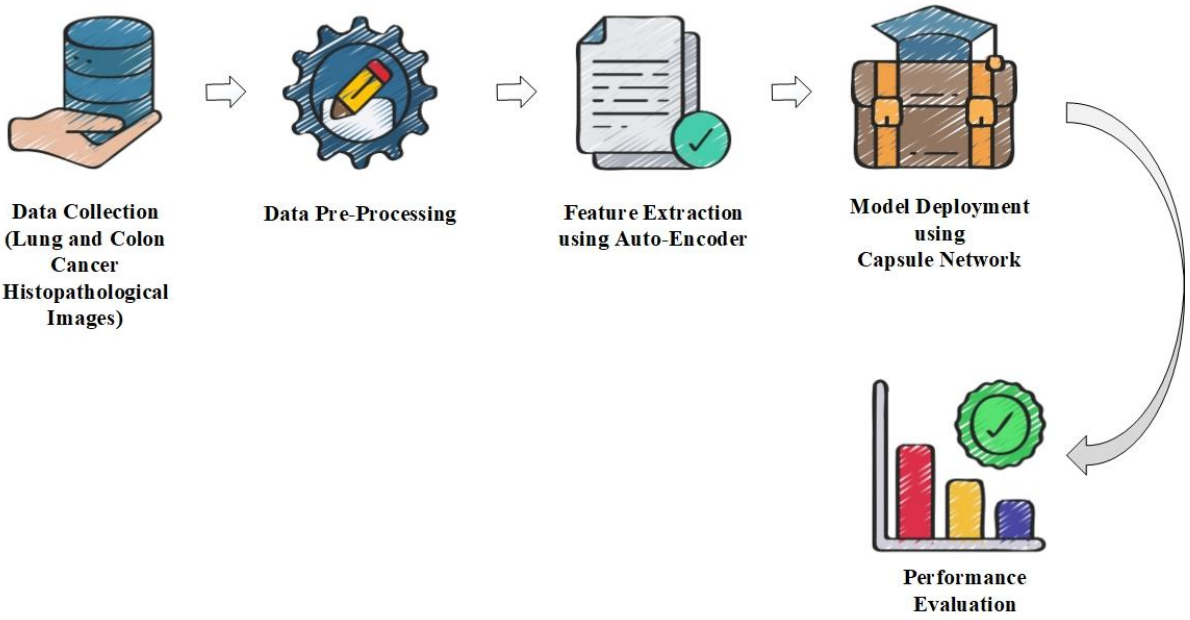

Fig. 1. Flow diagram of the proposed work.

B. Pre-Processing

It is common practice to pre-process histopathology images before delivering them to a machine learning model for examination. This entails a number of actions meant to improve the relevancy and quality of the raw photos. This procedure involves denoising as a way of reducing other unnecessary details which may probably hide other characteristics of the model, resizing of the photos to fit the model sizes and normalizing to ensure that pixel intensity levels are constant. Cleansing and normalizing, as well as pattern inclusion and non-biased, enhances the added images into the version and impacts definitely at the prediction algorithms utilized within the identity of such illnesses as lung and colon most cancers.

1) Normalization: One essential pre-processing method for getting histopathology images for ML is normalization. It is changing an images's pixel depth values to a standard scale, typically starting from 0 to 1, or to an average of zero and a general deviation of 1. Through this system, fluctuations in lighting fixtures, contrast, and coloration that can otherwise impair the model's performance are mitigated. Normalization guarantees that the model isn't impacted with the aid of unrelated elements and as a substitute concentrates at the pertinent aspects of the pics via normalizing the pixel values. In medical imaging, where constant image quality is crucial for precise analysis and diagnosis, this phase is especially crucial. Efficient normalization improves the precision and dependability of ML algorithms, resulting in improved lung and colon cancer detection and classification. Usually referred to as min-max normalization, the normalization formula is provided in (1),

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, the initial value of the pixel is X. The image's minimal pixel value is represented by X_{min}. The maximum pixel value in the image is represented by X_{max}. The normalized pixel value, X', will fall between 0 and 1.

C. Feature Extraction

Feature engineering is defined as data pre-processing to make it useful for the ML process and every business is now aware of the ability of ML to turn raw data into to a set of properties that can be useful in the construction of the model. Feature extraction in the case of histopathological images is about identifying and enhancing the salient features, that is, edges, textures, patterns and shapes that could indicate the presence or progression of the illness. Thereby, simplifying the data so that it can be more easily processed by computer models is the way in which the dimensionality is reduced. Thus, such methods as autoencoders might be applied to compress the image data into a lower-dimensional Latent space that maintains

the most important information. The thorough and precise feature extraction helps in enhancing the viability of the model's diagnosis and speed and its capability to categorize and predict ailments such as cancer of the lungs and colon.

1) Auto encoder: The goal of an autoencoder, a kind of artificial neural network, is to learn effective codings of input data through unsupervised learning. This is accomplished by first reconstructing the output from this representation after encoding the input into a latent-space representation. The encoder and the decoder are the two primary components of the network. The input is compressed by the encoder into a latent-space representation, which is then used by the decoder to recreate the input. Reconstruction error is to be minimized using an autoencoder in order to provide an output that closely resembles the input. This may be expressed quantitatively as reducing the mean squared error (MSE), or loss function L, between the input x and the reconstructed output xˆ in (2),

$$L(x, \hat{x}) = ||x - \hat{x}||^2 \quad (2)$$

The decoder function $x\ \hat{x} = g(h)$ maps the latent representation h back to the reconstructed input $\hat{x}$, whereas the encoder function $h = f(x)$ transfers the input x to the latent space h. The following is a summary of the complete process:

$$h = f(x) = \sigma(Wx + b) \quad (3)$$

$$\hat{x} = g(h) = \acute{o}(\acute{W}h + \acute{b}) \quad (4)$$

In Eq. (3) and (4) the weight matrices are represented by W and $\acute{W}$, the bias vectors by b and $\acute{b}$, and the activation functions by σ and $\acute{o}$. Typically, an autoencoder uses neural networks for both the encoder and the decoder, with training optimizing the weights to minimize the loss function. Autoencoders come in several designs, such as variational autoencoders (VAEs), denoising autoencoders, and sparse autoencoders, each intended for a particular use. Penalizing activations inside the hidden layers, sparse autoencoders ensure that the network learns more meaningful features by imposing sparsity restrictions on the latent space representation. This may be accomplished by including a regularization term that promotes sparsity in the loss function by (5),

$$L(x, \hat{x}) + \lambda \sum_i ||h_i||1 \quad (5)$$

Autoencoders with denoising competencies are made to address noisy information. To growth the resilience of the model, they're taught to recreate the authentic enter from a corrupted model of it. By first adding noise to the input records after which minimizing the loss characteristic between the easy enter and the output that become reconstructed from the noisy input, that is accomplished by way of (6),

$$L(x, \hat{x}) = ||x - \hat{x}_{noisy}||^2 \quad (6)$$

Fractional autoencoders (VAEs) are autoencoders with a probabilistic twist that makes them suitable for new data models. During training, a hidden signal is taken from this distribution, and the encoder outputs the parameters (mean and variance) of this distribution. Reconstruction loss along with a regularization term (KL deviation) that ensures that the reserved area distribution approximates all former distributions in the standard normal distribution of (7), forms the loss function in terms of VAEs

$$L(x, \hat{x}) = ||x - \hat{x}||^2 + KL(q(z|x)||p(z)) \quad (7)$$

In machine learning and data science, autoencoders are a vital tool because they can recognize useful representations of incoming data, facilitating streamlined and computationally efficient analysis. They are widely used for various tasks such as dimensionality reduction, anomaly detection, and generative modeling. In medical imaging, for example, it is used to extract key features from complex data, helping in tasks such as diagnosis and image reconstruction.

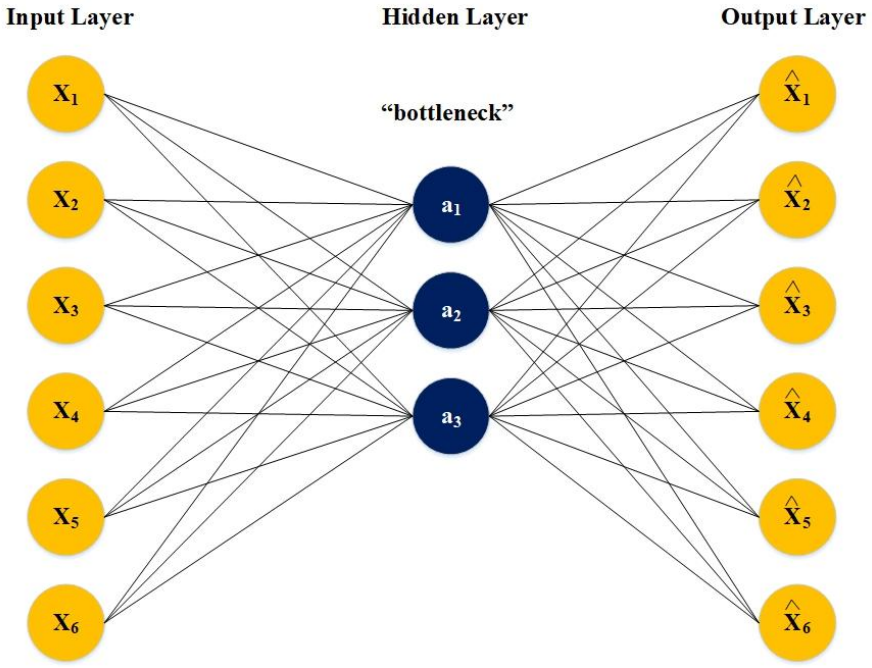

Fig. 2. Architecture of autoencoder.

Fig. 2 shows the autoencoder, a network that encodes raw input data through a series of hidden layers. The input layer receives unprocessed data, and its dimensionality is continuously reduced by the hidden layers, which identify significant patterns and characteristics. The last hidden layer, or bottleneck layer, is an indication of the input data's compressed encoding. The reconstructed output is created by the output layer, hopefully coming as near as feasible to the original data. at order to force the network to extract the most crucial features from the input data at the bottleneck layer, the autoencoder learns to reduce the reconstruction loss during training. Only the encoder portion of the autoencoder is kept after training in order to encode data that is comparable. The network is limited by regularization, denoising, short hidden layers, and activation function tuning. While adding a loss factor to the cost function encourages training in ways other than replicating the input, keeping each hidden layer as thin as feasible requires the network to take up only representative aspects of the data. Convolutional autoencoders enhance transmission and storage efficiency by reducing the dimensionality of high-dimensional image data. They are able to manage small alterations in object location or orientation and recreate missing components. Nevertheless, they have a tendency to overfit and may result in data loss, which compromises the quality of the reconstructed image. Proper regularization techniques are needed to address these issues.

The study focuses on improving colon cancer detection using CapsNets. Autoencoders play a crucial role in feature extraction from histopathological images. They reduce excessive-dimensional records to a lower-dimensional latent space, simplifying it for evaluation. The autoencoder extracts meaningful capabilities from the pics, identifying patterns, textures, and structural information indicative of cancerous and non-cancerous tissues. It also reduces noise by means of filtering out noise from histopathological pix. The autoencoder's potential to address records versions enhances the version's robustness. The autoencoder's preprocessing ensures the Capsule Network gets the maximum informative enter, improving its potential to correctly hit upon and classify cancerous tissues. This integration improves model accuracy and efficiency, leading to higher sensitivity and specificity. The autoencoder's position on this examine is to enhance early prognosis of colon most cancers through making sure specific and consultant features. Overall, the autoencoder enhances the accuracy, efficiency, and reliability of the most cancers detection model.

D. Capsule Network

A CapsNet is an artificial neural network (ANN) that imitates hierarchical connections through gaining knowledge of from the organizing concepts of biological mind systems. CapsNets are designed to mimic the hierarchical business enterprise of organic mind circuits. Basic building blocks known as tablets are used in a CapsNet to recover from regulations determined in conventional neural networks. Because tablet neurons consider each the spatial connections and the activation facts, they may be greater geared up to address changes in posture and hierarchical systems than normal neurons. Each capsule creates a collection of pose residences, consisting of orientation and position, collectively with an activation that represents a selected entity or part of an item. By enabling the network to iteratively modify the connection coefficients between them in response to the agreement of their posture parameters, capsules enable dynamic routing. Because of its ability to remember intricate spatial hierarchies and recognize subtle patterns in input, CapsNets enhance generalization. Capsules process inputs by affinely transforming the outcome into informative vectors, as opposed to neurons. Neurons function using scalars, whereas capsules use vectors. The processes involved in making artificial neurons include weighted connections, scalar activation, and sum computation. Capsules, on the other hand, undergo additional processes: input vectors are multiplied by weight matrices recorded with spatial relationships, further weight multiplication, weighted sum of input vectors, and vector output application of activation function.

1) Input vectors multiply with spatial-relationship-encoded weight matrices: The neural network's input vectors reflect the initial input or data from a previous layer. Weight matrices are multiplied across these vectors to change them. These weight matrices encode the geographical relationships within the data. When two objects are symmetrically positioned around each other and have similar dimensions, for example, the product of the input vector and weight matrix captures a high-level feature that describes this spatial arrangement. The neural network may identify and capture important correlations and features as it goes through its levels. In this instance, the weight matrix is being multiplied by the input vector.

2) Further multiplication with weights: In this phase, a capsule network's outputs from the preceding step undergo a weighted correction. While typical ANNs utilize error-based backpropagation to update weights, CapsNets use dynamic routing. The weights assigned to the synapses between neurons are determined by this unique procedure. CapsNets provide robust connections between nearby high-level and low-level capsules by dynamically changing their weights. The computation involves figuring out the precise distance between dense clusters indicating low-level capsule predictions and the outputs of the affine transform. These clusters develop and become closer together when low-level capsule predictions are comparable. As seen by the table, the high-level capsule nearest to the current prediction cluster has a bigger weight than the other capsules, which have smaller weights based on their distances.

3) Activation function application for vector output: Capsule activation functions ensure that vector outputs are dynamic and vividly represented. Squashing functions are a common choice since they preserve the vector's direction while restoring its length. The symbol for the Squashing Function is given in (8),

$$U_j = \frac{\|s_j\|^2}{1+\|s_j\|^2}\frac{s_j}{\|s_j\|} \tag{8}$$

where U_j is the output that results from applying the non-linearity function, and s_j is the sum of the input vectors. The vector s_j is compressed to a magnitude ranging from 0 to 1.

Because of this, strong hierarchical representations may be created by allowing capsules to record complex feature relationships. Because the squashing function normalizes data, it enhances resilience to changes and allows capsules to carry nuanced information necessary for complicated pattern detection in jobs like computer vision.

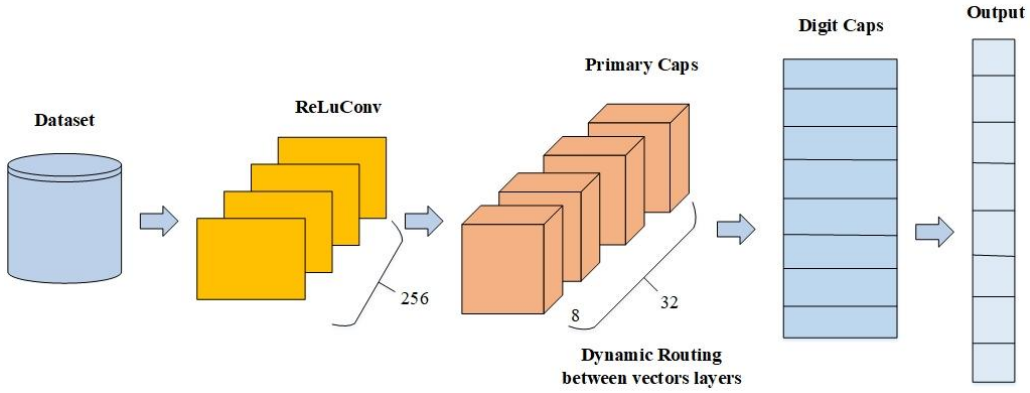

Fig. 3. Architecture of capsule networks.

Fig. 3 presents a simplified architecture of a capsule network that emphasizes the digit capsule and main layers. The input layer receives raw visual data and uses a convolutional layer to extract low-level features. After that, the main capsule layer processes the output and separates it into capsules. Each capsule produces an activation vector that indicates the existence of a particular characteristic or factor within its receptive field. The digit capsule layer, which represents a selected magnificence, is in rate of item popularity. The activation vector that every capsule produces indicates the likelihood that the class will seem in the photograph as well as its spatial connection to other components. An essential idea in CapsNets is dynamic routing, in which the primary pill layer casts votes to determine which digit pill it most carefully matches. This strengthens the settlement among compatible capsules and weakens the connections among incompatible drugs. Shooting the spatial hierarchy among functions, CapsNets are a type of neural community design that improves getting to know approximately representations. Because of dynamic routing, which makes it less complicated to attain an agreement on instantiation settings, they frequently require less information augmentation than conventional CNNs. Because CapsNets constitute vectors and routing systems, they're also more proof against adverse attacks. Additionally, they incorporate posture statistics, which complements structured representation for obligations like location estimation and item reputation.

CapsNets do have several drawbacks, though, including a lack of empirical assist, computational complexity, a probable tendency to overemphasize capsules, and intrinsic complexity. Given their latest age, CapsNets have not gone through calla lot checking out. Further research and evaluation are required to illustrate their typical effectiveness. Furthermore, due of dynamic routing, CapsNets may additionally require more processing power, main to longer training periods and better resource wishes. Applications for CapsNets may be observed in numerous domain names, which includes as clinical imaging, self-reliant vehicles, and visual anomaly detection. They are helpful in scientific imaging, assisting with troubles like organ segmentation and tumor identity. They also are useful in photograph popularity, item detection, region estimation, cybersecurity, and self-riding cars. Nevertheless, extra research and comparison are required to validate their ordinary effectiveness in diverse assignments.

The accuracy and robustness of histopathological image type are greatly improved with the aid of CapsNets inside the proposed study on boosting colon most cancers prediction the usage of CapsNets and Autoencoder-based totally function choice. CapsNets are particularly properly at retaining spatial hierarchies and connections within the image facts, which is vital for effectively recognizing difficult patterns that may be signs of malignant tumors. In evaluation to traditional CNN, which could have trouble processing orientation and attitude changes, CapsNets make better use of clusters of neurons called pills to capture and encode these spatial connections. As a result, they are able to discover characteristics at diverse abstraction stages and offer a greater complex interpretation of the photo statistics. The proposed examine makes use of CapsNets in conjunction with Autoencoders to extract features. This permits the Autoencoder to lessen dimensionality and emphasize pertinent features, whilst additionally utilising CapsNet's higher spatial awareness and sample popularity capabilities. This mixture improves the model's predictive potential, which might result in a greater specific and trustworthy categorization of histopathological photos for the identity of colon most cancers.

Algorithm 1: Algorithm for the Proposed study

Step 1: Data Collection and Preparation

- Load dataset of histopathological images
- Preprocess images

Step 2: Auto encoder for Feature Extraction

- Define Autoencoder architecture
  a. Input layer: X
  b. Encoding layers: progressively reduce dimensions
  c. Bottleneck layer: Z
  d. Decoding layers: progressively reconstruct dimensions
  e. Output layers: X’
- Split dataset into training and testing sets
- Train Autoencoder using mean squared error loss

- Extract compressed features Z from the bottleneck layer

Step 3: Capsule Network for classification

- Define Capsule network architecture
  a. Input layer: Z
  b. Convoutional Layer: extract local feature
  c. Primary Capsule Layer: convert features into capsules
  d. Digital Capsule Layer: from higher-level capsules
  e. Output layer: Class probabilities
- Combine Z with original image data
- Split combined dataset into training and testing sets
- Train capsule network using margin loss

Step 4: Integration

- Integrate Autoencoder and capsule network by feeding Z into the capsule network
- Fine-tune integrated model on training data

Step 5: Evaluation

- Validation and Testing
- Calculate Performance Metrics

V. Result and Discussion

The results of the advanced colon cancer prediction approach, which combines CapsNets with autoencoder-based feature selection, are shown in this section. The results show that this hybrid approach greatly improves the performance and reliability of the classification when compared to traditional techniques. The model makes the evaluation of histopathology images more reliable and consistent using the Autoencoder-based feature extraction with the help of the Capsule Network for determining the complex spatial relations. More details concerning the performance measures, benefits as well as the demerits of the model and how such developments aids in the early detection of colon cancer are demonstrated in this segment.

E. Training and Testing

The Fig. 4 shows the training and testing accuracy of a model over 100 epochs. The X-axis represents the number of training iterations the model has undergone, while the Y-axis represents the accuracy percentage. The figure shows the model's training accuracy on the training dataset and its testing accuracy on the testing dataset. The model's initial phase (0-20 epochs) shows rapid growth in both accuracies, indicating learning and improving performance on both datasets. The middle phase (20-60 epochs) shows slower growth in training accuracy, approaching a plateau around 60 epochs. Testing accuracy additionally improves but starts to lag behind the training accuracy, suggesting overfitting. The later phase (60-a hundred epochs) indicates an excessive schooling accuracy close to 100%, indicating superb performance on the schooling statistics. However, the trying out accuracy stabilizes at 85.9%, indicating overfitting. To cope with overfitting, techniques which include early stopping, regularization, or pass-validation could be implemented. The model's testing accuracy stabilizes at a high stage, indicating top overall performance, but there may be room for development in generalization. To deal with overfitting, techniques which include early preventing, regularization, or go-validation can be applied.

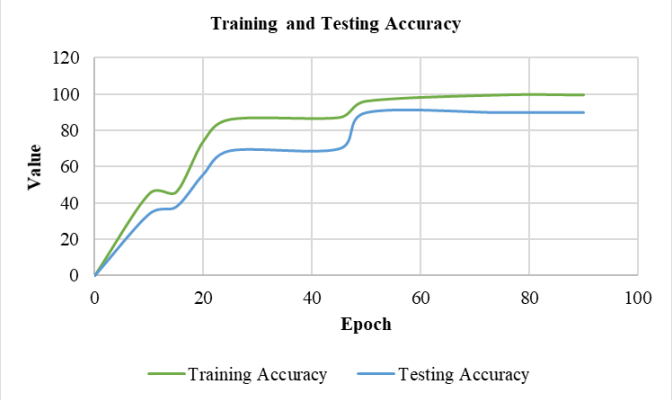

Fig. 4. Training and testing accuracy

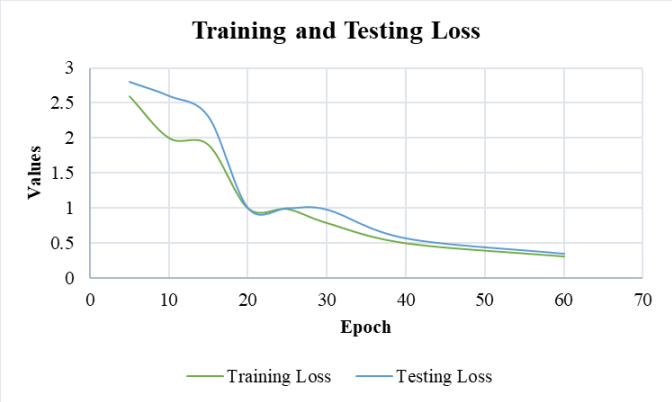

Fig. 5. Training and testing loss.

The Fig. 5 shows the training and testing loss of a version over 60 epochs. The X-axis represents the variety of schooling iterations, at the same time as the Y-axis represents the loss cost, which measures the error between anticipated and real values. The figure shows the lack of the model at the dataset and the loss at the testing dataset. The analysis shows that the version is getting to know efficiently and both training and trying out losses are decreasing, indicating top generalization overall performance. The initial phase (0-20 epochs) shows fast decreases in both losses, at the same time as the center phase (20-40 epochs) indicates a gradual lower in schooling loss and a slow lower in testing loss, indicating accurate generalization but signs of overfitting. The later phase (40-60 epochs) shows a solid and convergent loss, suggesting that the model has reached a superior point wherein further schooling does no longer significantly improve performance or motive overfitting. The graph concludes that the model is nicely-trained, achieving low mistakes charges on each schooling and trying out datasets. The near convergence of training and checking out loss in later epochs shows that the model isn't overfitting notably, maintaining true generalization performance. The stability and convergence of loss values in later epochs recommend an awesome balance among bias and variance, minimizing underfitting and overfitting.

F. Performance Metrics

Performance metrics are numerical measurements which are used to evaluate how a model or gadget plays in achieving its goal. These measures, which are relevant to ML and diagnostic

model, consist of F1 rating, accuracy, precision, and recall. TP as true positive, TN as true negative, FP as false positive, and FN as false negative are represented.

1) Accuracy: A performance statistic called accuracy counts how many of a model's predictions are accurate out of all the predictions it has made. It is computed in (9),

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

2) Precision: A performance indicator called precision counts the percentage of accurate positive predictions among all the positive predictions a model makes. It is computed in (10),

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

3) Recall: Recall quantifies the percentage of real positive cases that a model accurately detects; it is sometimes referred to as sensitivity or true positive rate. It is computed in (11),

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

4) F1 score: The F1 score is a performance statistic that offers a fair assessment of a model's accuracy by combining recall and precision into a single number. This provides a more thorough understanding of a model's performance, particularly when working with unbalanced datasets. It is the harmonic mean of accuracy and recall. The F1 score is calculated in (12),

$$F1 = \frac{Precision.Recall}{Precion+Recall} \quad (12)$$

Table I show that colon most cancers prediction with CapsNets and Autoencoder-based feature selection has extraordinary model performance. The model efficaciously classifies 99.2% of the cases with an accuracy of 99.2%, indicating its efficacy in distinguishing among samples which are malignant and people that aren't. The model's 99% accuracy suggests that it could reliably pick out affirmative conditions with few fake positives. The model's capacity to minimize fake negatives while catching the majority of real occasions is demonstrated with the aid of its 98.3% recall. The alternate-off among accuracy and reminiscence is balanced by means of the F1 score, that is 98.6% and represents the harmonic suggest of precision and recall. The resilience and dependability of the model in processing histopathological images are highlighted by those sturdy metrics. Specifically, the accuracy validates the effectiveness of merging Autoencoders with CapsNets, which effects the cautioned observe. It attests to the model's capability to both recognize the complex styles seen in the education set and generalize successfully to new units of records. Because of its brilliant accuracy, the version may be carried out nearly in clinical settings and can assist identify colon cancer early on, growing patient consequences and remedy options.

TABLE I. PERFORMANCE METRICS OF THE PROPOSED STUDY

Metrics	Efficiency
Accuracy	99.2%
Precision	99%
Recall	98.3%
F1 score	98.6%

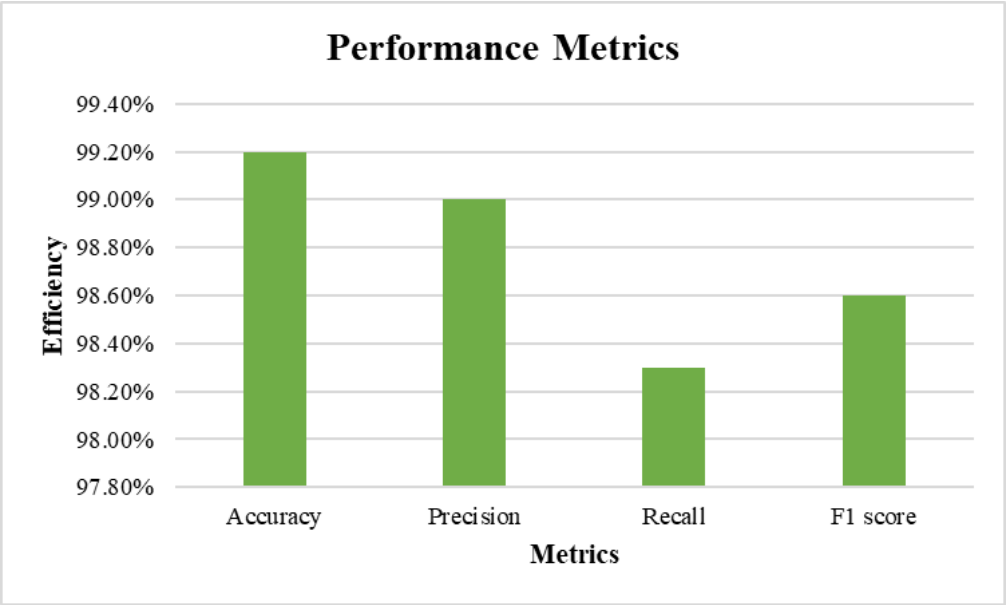

Fig. 6. Performance metrics of the proposed study.

The accuracy, precision, recall, and F1 score of the suggested colon cancer prediction model are highlighted in the Fig. 6 that displays its performance measures. At around 99.2%, the accuracy is the greatest, meaning that 99.2% of all cases are accurately classified by the model, demonstrating its overall efficacy. With 99% precision, only 99% of cases accurately categorized as positive are actually positive, reducing the number of false positives. With a little reduced recall of 98.3%, the model reduces the amount of false negatives by capturing 98.3% of all real positive cases. The F1 score, which is 98.6% and represents the harmonic mean of precision and recall, is a balanced measure of the model's accuracy that accounts for both precision and recall. Taken together, these parameters demonstrate the model's accuracy in colon cancer prediction from histopathological images as well as its dependability. The model's excellent accuracy confirms that it can generalize from training information to unseen test data, which is necessary for its application in real-world clinical settings. In clinical circumstances, it might be advantageous to prevent needless treatments by emphasizing the reduction of false positives over the capture of all real positives, as indicated by the minor decline in recall when compared to precision. The model's well-balanced performance is shown by the F1 score's proximity to both accuracy and recall. The model is robust in learning and identifying complex patterns in histopathological images, and it is also dependable in making accurate predictions, which may lead to improved early detection and diagnosis of colon cancer. This is indicated by the high accuracy and balanced precision-recall performance. Better patient outcomes and more effective clinical decision-making procedures might result from this.

The efficacy metrics of many colon cancer detection techniques are displayed in Table II. With 85% accuracy, 80% precision, 75% recall, and 77% F1 score, logistic regression offers a basic method but falls short in terms of sensitivity and overall effectiveness. Decision trees perform better but still fall short when compared to more advanced techniques, with 87% accuracy, 83% precision, 80% recall, and an 81% F1 score. Results are further improved by Random Forests, which show good overall performance with 90% accuracy, 87% precision, 85% recall, and an 86% F1 score. Gradient Boosting Machines show notable advances in identifying and categorizing malignant cells, achieving superior performance metrics with 93% accuracy, 90% precision, 90% recall, and a 91% F1 score. On the other hand, the suggested approach, which combines autoencoder-based feature selection with CapsNets, yields remarkable outcomes with 98.6% F1 score, 99% precision, 98.3% recall, and 99.2% accuracy. This strategy uses cutting-edge ML algorithms to improve feature extraction and pattern recognition, outperforming all other approaches and demonstrating its improved capacity to consistently and effectively diagnose colon cancer.

TABLE II. COMPARISON OF PROPOSED METHOD WITH DIFFERENT METHODS

Method	Accuracy	Precision	Recall	F1 Score
Logistic Regression [17]	85%	80%	75%	77%
Decision Trees [18]	87%	83%	80%	81%
Random Forest [19]	90%	87%	85%	86%
Gradient Boosting Machines [20]	93%	90%	90%	91%
Proposed Method	99.2%	99%	98.3%	98.6%

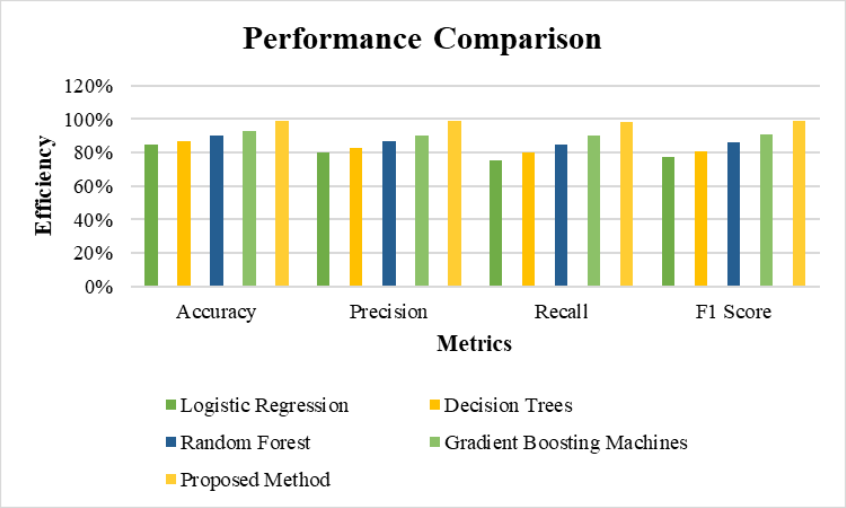

Fig. 7. Performance comparison of the proposed method with different methods.

Fig. 7 showcases a performance comparison of ML algorithms, including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting Machines, and the Proposed Method. The x-axis displays metrics like accuracy, precision, recall, and F1 Score. The Proposed Method have the highest accuracy, precision, recall, and F1 Score and consistently performs well across all metrics, while Random Forest also shows strong performance in most metrics. However, it is challenging to provide a definitive interpretation without specific values and context. The visualization suggests the Proposed Method might be a promising approach, but further analysis and understanding of the data are necessary. The exact

meaning of Efficiency on the y-axis is unclear, and the dataset and problem domain used for this comparison are unknown, limiting broader conclusions.

TABLE III. COMPARISON OF PROPOSED DATASET WITH DIFFERENT DATASETS

Dataset	Accuracy	Precision	Recall	F1 Score
Gapminder Colon cancer [21]	85%	80%	75%	77%
Colon cancer [22]	87%	83%	80%	81%
Multi Cancer Dataset [23]	90%	87%	85%	86%
ICMR Dataset [24]	93%	90%	90%	91%
Lung and Colon Cancer Histopathological Images	99.2%	99%	98.3%	98.6%

The Table III compares many datasets that have been used to assess alternative approaches to the diagnosis of colon cancer. An F1 score of 77%, recall of 75%, accuracy of 85%, and precision of 80% were attained using the Gapminder Colon cancer dataset. With an F1 score of 81%, accuracy of 87%, precision of 83%, and recall of 80%, the Colon cancer dataset demonstrated increased performance. The metrics were further improved by the Multi Cancer Dataset, which achieved an F1 score of 86%, 90% accuracy, 87% precision, and 85% recall. With an F1 score of 91%, accuracy of 93%, precision of 90%, recall of 90%, and recall of 90%, the ICMR Dataset performed even better. With an amazing accuracy of 99.2%, precision of 99%, recall of 98.3%, and an F1 score of 98.6%, the suggested technique surpassed all other methods when evaluated on the Lung and Colon Cancer Histopathological Images dataset, demonstrating its better capabilities in diagnosing colon cancer.

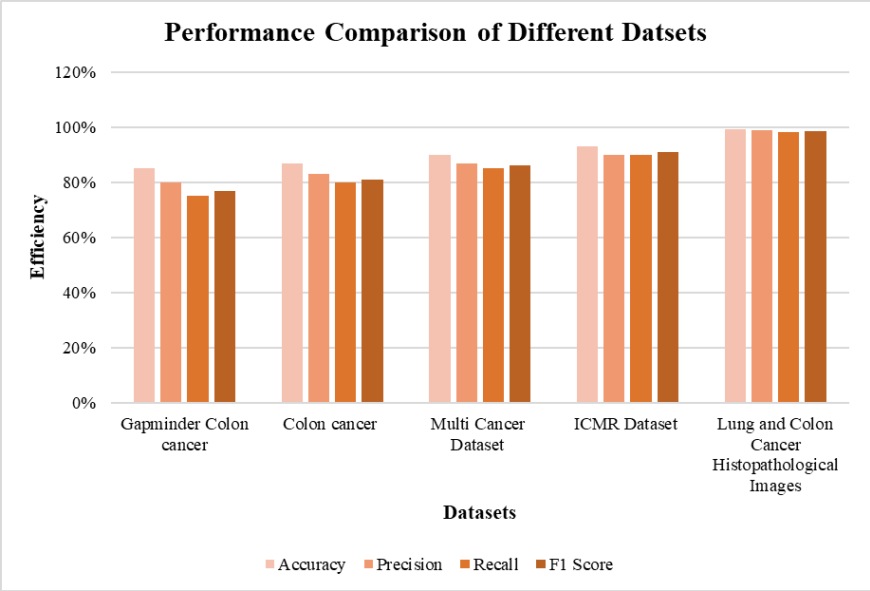

Fig. 8. Performance comparison of the proposed dataset with different datasets.

Accuracy, precision, recall, and F1 score are the four main metrics that are highlighted in the Fig. 8, which presents a visual comparison of the performance of different datasets used in colon cancer diagnosis. The least successful dataset is the Gapminder Colon Cancer dataset, which has an F1 score of 77%, recall of 75%, accuracy of 85%, and precision of 80%. With the Colon cancer dataset, performance somewhat increases to 87% accuracy, 83% precision, 80% recall, and 81% F1 score. These measures are further improved by the Multi Cancer Dataset, which achieves an F1 score of 86%, 90% accuracy, 87% precision, and 85% recall. With 91% F1 score, 90% precision, 90% recall, and 93% accuracy, the ICMR Dataset shows even better efficiency. With accuracy at 99.2%, precision at 99%, recall at 98.3%, and an F1 score of 98.6%, the suggested method which makes use of the Lung and Colon Cancer Histopathological Images dataset achieves the best results in terms of all metrics, demonstrating its better capacity to identify cancer accurately.

G. Discussion

Previous studies of colon cancer detection often struggled with the accuracy and reliability of their models. Although, traditional methods such as decision trees and logistic regression had stability and accuracy problems that increased the number of false negatives and positives Strong models needed for the accuracy of the analysis cannot be fully captured and often requires significant feature engineering [25]. The proposed method uses auto-encoder-based feature selection combined with CapsNets to address these limitations. The ability of CapsNets to preserve spatial structure and detect small patterns is essential for accurate cancer diagnosis. On the other hand, autoencoders enhance feature extraction by reducing noise and compressing high-dimensional data into a feasible hidden area that highlights some important features and most of them were captured there with significant improvements occur in accuracy, precision, recall, and F1 scores It occurs as analyzed hereafter. This approach addresses and improves the weaknesses of

existing methods, thereby providing more accurate and rapid detection of colorectal cancer that can change clinical diagnosis.

VI. Conclusion and Future Work

Research suggests that the combination of autoencoder-based feature selection and CapsNets might greatly improve the accuracy of colon cancer prediction using histopathological images. Because of the CapsNets' spatial hierarchy learning and autoencoders' strong feature extraction capabilities, this model is more successful in correctly identifying malignant tissues. Using a hybrid technique, frequent problems like overfitting are successfully reduced, classification accuracy is increased, and the model's ability to generalize from training to new data is encouraged. The findings imply that this sophisticated machine learning model has great promise for clinical use, where accurate and prompt diagnosis of colon cancer is essential for efficient treatment planning and better patient outcomes. This effective use of contemporary deep learning architectures highlights how various methods may be used to address difficult classification problems in medical image analysis.

Improving the model's flexibility and reactivity to various clinical settings should be the main goal of future research. This involves looking at cutting-edge data augmentation methods to strengthen the model's resistance to changes in the quality and quantity of histopathology images. Furthermore, investigating the incorporation of additional datasets, such genetic data or patient medical history, may provide a more thorough method of cancer diagnosis and prognosis. To fully assess the model's performance and potential, it is also crucial to apply it in actual clinical situations. Extending the study's reach will showcase the adaptability and usefulness of the concept. Lastly, to guarantee that the model satisfies clinical requirements and keeps improving patient outcomes and care, continuous cooperation with healthcare professionals is crucial.

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