AI-Powered Histopathological Analysis for Intelligent and Early Detection of Colon Cancer: A Synergistic Approach with Inception v3 and Machine Learning

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***Abstract*—Colon Cancer (CC) is one of the major global concerns, as it is the third most common cancer worldwide and nearly 10% of all cancer cases. The mortality rate of this cancer is also high. Age and sedentary lifestyle are the two major causes of this cancer. Colon cancer does not show any significant signs of detection at the early stage. Advanced stages of diagnosis leave with very few treatment options. It is for this reason that Artificial Intelligence (AI) can step in to identify the disease at an early stage. Integrating AI with a screening of Histopathological Images will aid in intelligent colon classification. This technique will streamline the process, saving time and maximizing the expertise of medical professionals. In the proposed approach, Deep Learning (DL) based Inception v3 model (IV3M) is integrated with three Machine Learning (ML) models like Neural Network (NN), Gradient Boosting (GB), and Decision Tree (DT) for an automated colon classification. Integrating DL and ML can solve the complex in understanding histopathological images and further aid in the classification process. Achieving 98.8% classification accuracy, our method shows a 10.93% improvement over ANN, 6.88% over BPNN, and 7.89% over Convolutional Neural Networks (CNN). The results are validated using 10-fold cross-validation done on the dataset. Results are further validated by Confusion Matrix (CM), Calibration Plot (CP), and Receiver Operating Characteristic (ROC) Analysis. Integrating DL and ML for CC classification has the potential to reform clinical practice by saving lives with more accurate prediction and optimizing healthcare resources. For clinical purposes, experts like gastroenterologists and Colon surgeon must be consulted for the necessary diagnosis. The paper intends to provide a dedicated technique for the classification of colon cancers at an initial stage, so as to offer patients with the early possible treatment options.**

***Keywords*—deep learning, machine learning, colon cancer, neural network, gradient boosting**

I. Introduction

Colon Cancer is one of the most common types of cancer that can develop in people of all ages. It is also one of the leading causes of death globally [1]. Everyone is born with a colon. It is an organ there in the lower area of the stomach. It is also called the large intestine. Rectum is another organ in the lower part of the digestive tract. Rectum is a small tube and together the colon and rectum are 1.5 to 2 m in length.

Colon is a part of the human body that is associated with the digestive system. Food goes from the mouth, esophagus, stomach, small intestine, and then to the large intestine. In the mouth food is chewed, chewed food also called a bolus then travels through the esophagus, the bolus is further broken by enzymes and acids of the stomach, and nutrients get absorbed in the small intestine. After food is digested, the solid and liquid part are separated by colon. Finally, the waste material gets collected in the colon and then comes out in the form of excreta.

When the cells in the colon become abnormal and grow out of control then CC happens [2]. It is sometimes called colorectal cancer. This name involves both colon and rectum cancer. CC starts to emerge in the form of polyps [3] in the colon. It is from some of these polyps that CC develops. Polyps are in the form of hanging lumps, flat lumps, or any shape lumps in the colon. Since these polyps do not show any sign of presence in the body, screening is the only form of detection of polyps.

When a CC patient goes to the doctor, asks about the reasons why he or she got such a cancer. There is no particular reason for CC, but the factors may be many. Although CC can happen at any age, studies have found out that with increasing age the chances of CC rise. Sedentary lifestyle, diabetes, and obesity increase the risk of CC. Drinking and smoking also increase the chances of CC. A family history of CC could be another reason for the existence of disease [4].

Lynch syndrome could be another reason for CC [5]. In this syndrome, mutations in genes are responsible for the occurrence of the disease. Familial Adenomatous Polyposis (FAP) [6] is yet another inherited gene mutation responsible for happening of the disease. In FAP, polyps start to develop when a person is young. And by the age of nearly 40, he or she has a 100% chance of developing CC.

Common symptoms of CC [7] include transformed bowel behavior such as constipation, the feeling of incomplete passing of stool, diarrhea, etc. Apart from this, blood coming in stool, bloating, and pain in the lower abdomen are a few other symptoms. Blood coming in stool may be visible or alternatively, it is occult blood, i.e., blood is there in stool but it is not visible by the naked eye, rather the presence of blood is known in the lab tests only. In elderly people with occult blood and iron deficiency, the chances of CC are higher. Fatigue, weight loss, and reduced appetite are a few other symptoms.

Colonoscopy is the best method for the diagnosis of CC [8]. Colonoscopy is done after cleaning the bowel and sedation. Due to sedation, the patient does not feel any pain during the screening process. If during the process of screening, the experts want to confirm that CC is there or not, then a biopsy is done of the suspicious areas. The presence of cancer is confirmed after microscopy is done in a lab test. In some countries, it is mandatory to go for a colonoscopy after the

age crosses 50.

Fibre [9] rich diet which includes wheat, fruits, vegetables, etc. reduces the risk of CC. Western diet, which includes red meat, increases the chances of the CC. Heavy drinking of alcohol and smoking should be avoided. Proper exercise should be done by patients. One should also try to reduce weight and control blood sugar. All these eating habits will definitely give a strong immunity to the person with or without CC.

CCs are treatable. Once the CC is diagnosed then staging is done to identify the spread of the cancer [10, 11]. In this process, Computed Tomography (CT) scans of chest and abdomen are done. For rectal cancer, Magnetic Resonance Imaging (MRI) and Endoscopic Ultrasound (EUS) are done. A team of doctors and experts is formed for the treatment of CC which includes gastroenterologist, gastroenterologist surgeon, medical oncologist, radiation oncologist, pathologist, and radiologist, etc. Dietitian, nutritionist, and physiotherapist are also included in the team.

First of all, it is to identify where the CC is. It may occur in the colon or in the rectum. Treatment is different in both cases. Treatment of rectum cancer depends on the stage of the cancer. Early-stage rectum cancer can be treated by endoscopy. If the rectum tumor is locally advanced, then first chemotherapy and then radiotherapy is given. After the downstaging of the tumor, surgery is done. If the rectum cancer has spread to other parts of the body, then chemotherapy is done and sometimes a stent is put in the rectum for easy bowel movement. Sometimes, there is a fear in rectum cancer patients that they have to put on a colostomy bag for their whole life. If the rectum cancer is 2 cm above the anus, then there is less chance of putting a colostomy bag.

If the CC is confined to colon only, then the first surgery is done, and then chemotherapy is given depending on the nature of the cancer. Alternatively, if CC spreads to other parts of the body, then chemotherapy is done first and then the local surgeries can be done for the removal of the cancer. Sometimes stent is also put up in the colon for ease of bowel movement. Once a patient gets the necessary treatment related to CC, still there are chances of developing of new CC. So regular screening is advisable for such patients.

In this paper, we will be integrating AI tools using Deep Learning (DL) and Machine Learning (ML) for classifying the CC in an automated manner. The paper is organized by giving an introduction in Section I. Literature review is specified in Section II. DL and ML methods are discussed in Section III. The proposed methodology is discussed in Section IV. Experimental results are shown in Section V. The concluding remarks are arranged in Section VI.

II. Literature Survey

A technique for detecting CC was proposed by Srivani and Seshikala [12]. It is stated in the paper that CC happens to be the third major cause of mortality in cancer-related disease. Deep Learning (DL) techniques are used for intelligent CC diagnosis. It is suggested in the paper that early diagnosis of CC is necessary for better treatment. Rathore *et al.* [13] suggested a technique of CC classification based on Ensemble Learning (EL). Gene Expression (GE) parameter is taken for CC identification. A variation in GE shows the presence of CC. Two sets of classes are taken in the classification. One is a normal class and the other is a malignant class. Feature extraction techniques are employed along with the ML algorithm, i.e., Support Vector Machine (SVM). A majority voting technique is used in EL.

Lung and CC detection technique is proposed by Mehmood *et al.* [14]. Histopathology images of lung and cancer form the dataset for the given technique. 2500 images are taken for the training of the model. A modified version of AlexNet was used in the proposed work. The accuracy of the model obtained after experimentation was 89%. Certain pre-processing techniques were also employed for reduced quality images. Zhang and Xing [15] suggested a technique for CC identification using DL. The paper suggested screening to be a crucial part in the diagnosis of the disease. A change in the structure of genes is considered in this paper. Structural and non-structural features are identified for determining the classification accuracy. Random Forest (RF) algorithm is finally used to determine the class under which the disease falls.

An integrated ML and DL framework is given by Fadel *et al.* [16]. The work suggested identifying numerous types of cancer using the proposed model. It is stated in the paper that every sixth death in the world happens due to cancer. Employing DL techniques is advantageous as a large amount of data can be analyzed in no time. A modified form of the Whale Optimization algorithm was used in the proposed research. In 2019, Sari and Demir [17] suggested a technique for the classification of Histopathological images. Unsupervised feature extraction was used in the given work. The best technique for diagnosis of cancer is suggested to be Histopathological examination. Manual identification involved in the process of disease identification was time consuming and errored. Restricted Boltzmann Machines (RBM) algorithm was used to automate the process of classification.

A DL-based technique for identification of polyps was suggested by Jia *et al.* [18]. It was suggested in the paper that the identification of polyps is crucial for CC diagnosis. It is stated that a new tool termed wireless capsule endoscopy leads to better visualization of CC and causes less discomfort to the patients. Alboaneen *et al.* in 2023 [19] reviewed various ML and DL algorithms that may be useful for CC identification. Three sections for each algorithm include the objective of the prediction, the technique involved, and the dataset. Histopathology images, colonoscopy images, and radiology images are reviewed in the dataset.

A CNN-based classification of CC was done in an automated manner by Hasan *et al.* [20]. Histological images were taken in the dataset. Certain pre-processing techniques were also applied to the images. Benign and malignant classes were considered for categorization purposes. Computation time and the cost factor were also considered in the paper. A multi-center study on CC was given by Jiang *et al.* in 2024 [21]. An attention-based model was used for the diagnosis purpose. Patient data was taken from four different countries. Survival rates were also predicted in the outcome. It is suggested by the paper to include AI algorithms for clinical implementations on CC.

A Lung and CC classification mechanism was given by Ofary *et al.* [22]. Three DL models were used in the first phase which includes SqueezeNet, AlexNet, and ShuflleNet.

SoftMax function was used for evaluation metrics. In the second phase, the output obtained was fed to the SVM classifier. In the next phase, a Principal Component Analysis framework was used to reduce the number of features. In the final phase, again SVM is applied to improve accuracy.

Ramesh and Savithri [23] gave a technique for CC detection. The Yolov5 model is used in the research work. More than 2000 images were included in the dataset. 78 min is the computation time that was observed while training of data. The anticipated technique aids classifying the tumor cell into benign and adenocarcinomas. A CC detection-based technique was proposed by Swarna and Hashi [24]. Ensemble Learning and Inception V3 models were used in this work. More than 10K images were used in the dataset for training and testing purposes. A high accuracy of 99.5 was observed for the given models.

III. Integrating DL and ML Algorithms for Colon Cancer Classification

In the proposed work, we have used one DL and 3 ML models. The DL model used in this work is the Inception v3 Model (IV3M) as shown in Fig. 1. IV3M is a pre-trained model designed by Google for DL tasks. The model is trained on the ImageNet Dataset. The model can identify features from different types of classes and is trained on millions of images. In this work, we will be using IV3M for Colon Cancer Classification. IV3M is an advanced CNN-based architecture. In this factorization of convolutions are done, so as to reduce computational complexity. The model is 92 MB in size with top 5 accuracy of 93.7%. Multiple blocks called inception modules are stacked together. Overfitting and computational complexity are greatly reduced by using IV3M.

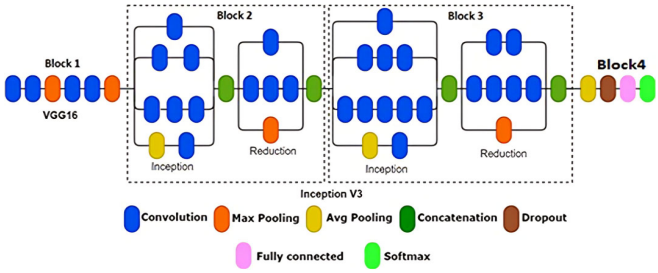


Fig. 1. Inception v3 model [25].

The first ML model used in this work is a Neural Network (NN) model called Multi-Layer Perceptron (MLP) with backpropagation as shown in Fig. 2. It has the ability to learn from linear as well as non-linear data. We have used 100 neurons in the hidden layer. Rectified Linear Unit (ReLU) is used as an activation function in this model. Adam optimizer is used to train the model with an L2 regularization value of 0.0001. This value will prevent overfitting and generalizing the model. The weights get updated by identifying the errors with the maximum number of iterations of 200.

The second ML model used in this work is Gradient Boosting (GB) as shown in Fig. 3. It is based on multiple decision trees. The number of decision trees used in this work is 100 with a learning rate of 0.100. Multiple weak trees are combined to form a stronger one. For growth control, we have limited the depth of individual trees to 3. A node can have a maximum of two data points in the split. Subsampling is set to 1.0 which determines the proportion of the training data used to fit each individual tree.

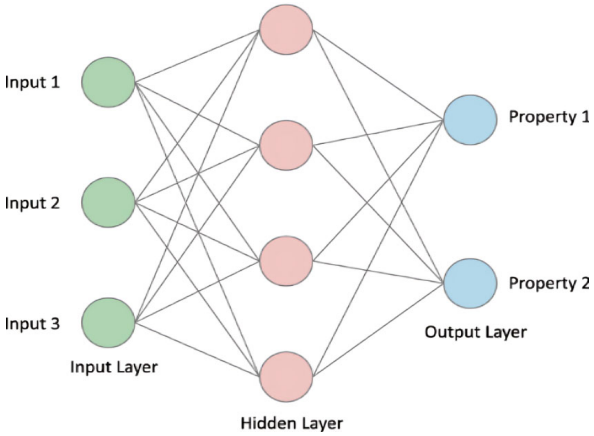


Fig. 2. Multi-Layer perceptron [26].

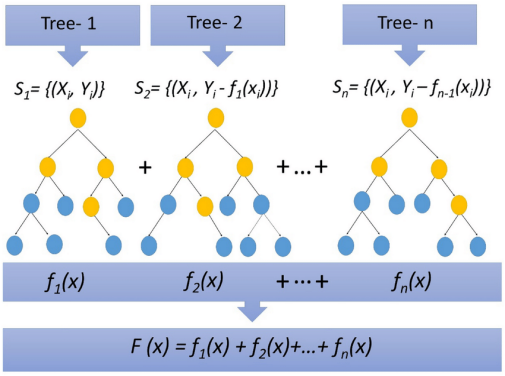


Fig. 3. Gradient Boosting [27].

The third ML model used in this work is Decision Tree (DT). At each level in the DT, the best attribute is selected using Attribute Selection Measure (ASM). The two prevalent practices for ASM include Information Gain (IG) and Gini Index (GI). The higher the value of the IG, the better the attribute that can be selected for splitting the dataset. GI is another measure for attribute selection which is computationally efficient in comparison to that of IG.

Integrating DL and ML can solve the complexing in understanding of histopathological images and classification. With DL, hidden patterns and relationships among histopathological images can be extracted. Computational efficiency in terms of time and effort will be reduced. Unstructured data like images and structured data like feature maps obtained from them can be handled expertly. With ML algorithms classification can be done efficiently.

Inception V3 model will extract the high-level features from histopathological images of colon cancer. The extracted features will be transformed into numerical vectors for capturing essential patterns. This vector will then act as input to classification algorithms like Neural Networks, Gradient Boosting, and Decision Tree for classification purposes. AI techniques proposed in the research paper will improve the chances of successful treatment as there is an enhancement in accuracy and efficiency of detecting the disease at an early stage. AI can assist in the reduction of the overall cost of colon cancer screening and diagnosis. This will further boost the increase of survival rates and thus an improved quality life. Methodology used for the given research work is given in the next section.

IV. Methodology

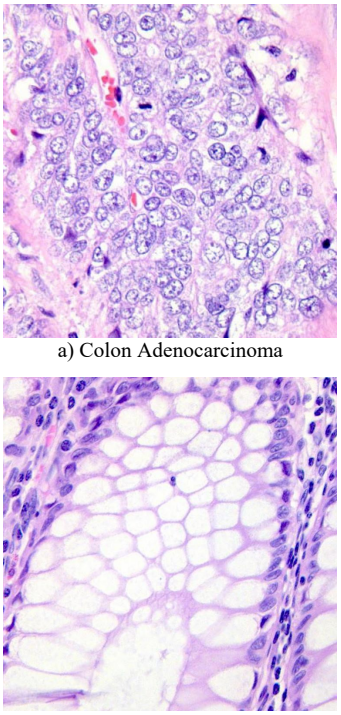
In the proposed research work, preprocessing techniques incorporated are Data Collection and Annotation of histopathological images of colon cancer, Image Normalization to standardize the color distribution, Rescaling to a size of 768×768 pixels, and finally splitting the dataset into training, validation, and test sets.

For model training, transfer learning with pre-trained Inception V3 is used to enhance the feature extraction capabilities. During training optimization of the model is done using the stochastic gradient descent technique. Finally, hyperparameter tuning is done to determine the learning rate, batch size, and number of epochs.

Evaluation parameters identified include classification accuracy which identifies the correctly classified images out to the total images. Precision gives the proportion of true positives among predicted positives, Recall gives the proportion of true positives among actual positives, F1-Score gives the harmonic meaning of precision and recall. The ROC curve illustrates the trade-off between true positive rate and false positive rate. Finally, Confusion Matrix is used to identify true positives, true negatives, false positives, and false negatives.

A. Dataset

The dataset that is used for research purposes comprises of Histopathological Images (HI). The dataset is available in public domain for research purposes [28]. HI images are vital in diagnosing CC. Depending on the shape and structure of the cells, it is detected whether the cells in the images are cancerous or not. 200 HI images are taken in this work. These images are divided into two sets. One set contains 100 images of Colon Adenocarcinoma (CACA) and another set of 100 images of Colon Benign (CB). One image of each set is depicted in Fig. 4.



a) Colon Adenocarcinoma

b) Colon Benign

Fig. 4. Categories of histopathological images [28].

B. Experimental Model Workflow (EMW)

EMW for the proposed research work is given in Fig. 5. An integrated process of DL and ML Learning for intelligent CC classification is being done in this technique. Learning from various features, shapes, and structures present in HI is carried out using Inception V3 algorithm. The result of this DL-based CNN is carried further to ML algorithms. These algorithms include NN, GB, and DT. CC classification is carried out by these algorithms. Output, generated by the ML algorithms, are further assessed using Evaluation Metrics, ROC Analysis, Calibration Plot (CP), and Confusion Matrix (CM).

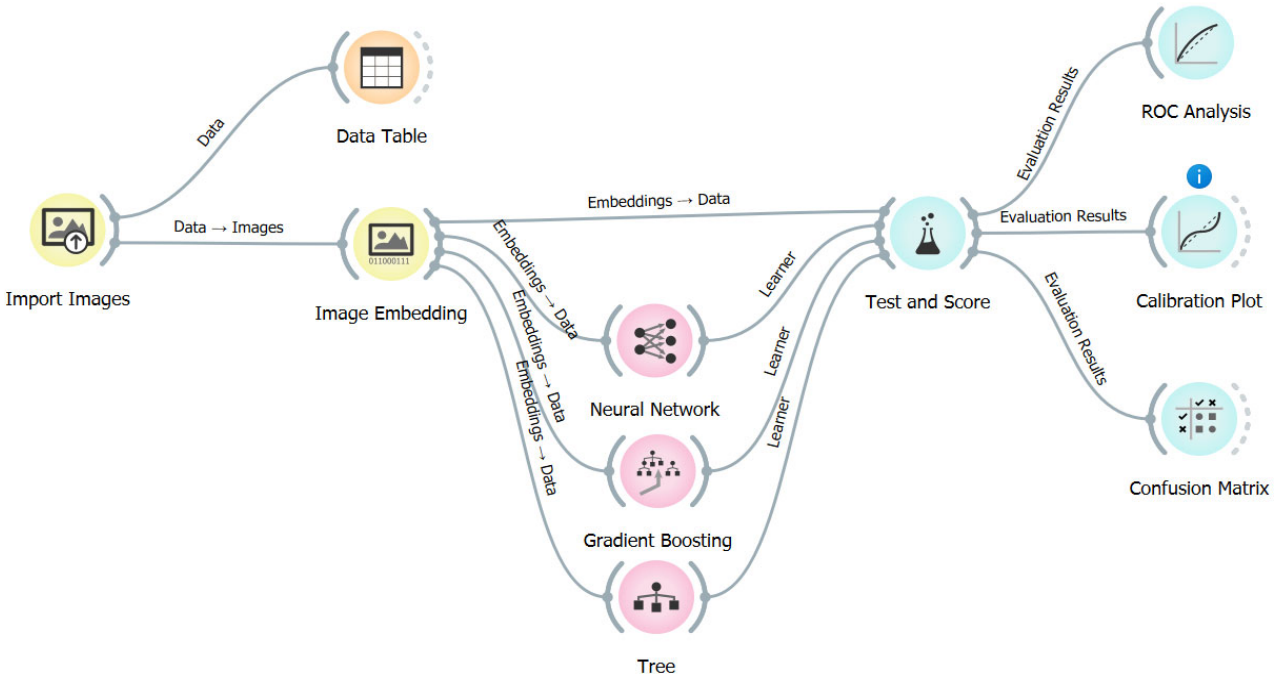


Fig. 5. Experimental Model Workflow (EMW).

Various Steps (S) of EMA include:

- In S1, HI is imported from two subfolders.
- In S2a, all the two hundred instances of images are shown in the form of a table. Category, image name, image path, size, width, and height are the parameters of this Data Table. There are 5 meta-attributes and one target, i.e., colon classification with two values.
- S2b is image embedding using Deep Neural Networks. All the 200 images are represented in the form of a vector of numbers. Inception V3 model is used to calculate the feature map w.r.t. each image.
- The vector of numbers is fed to 3 ML models in S4. NN, GB, and DT models do the task of classification of HI.
- S5 involves Tests and Score. Stratified sampling is done in the cross validation, with number of folds taken to be 5. The training set size of 66% is taken while remaining 34% set is taken for testing part. Evaluation results for target variable are computed at this step.

In S6, CM, CP, and ROC Analysis is done, to visualize and validate the results. Parameters of the Neural Network include the Number of Neurons in the Hidden Layer: 100; Activation Function: ReLU; Solver: Adam; Regularization: 0.0001; Maximum number of iterations: 100; Replicable training is included to ensure consistency and reproducibility of the training process.

Parameters of Gradient Boosting include scikit-learn library; Number of Tress: 100; Learning Rate: 100; Depth of Individual Trees:3; Splitting limit: 2; Fraction of Training Instances: 1.00.

Parameters of Decision Trees include Binary Tree; Min. Number of Instances in Leaves: 2; Splitting Limit: 5; Max. Tree Depth: 100; Classification Majority Selection: 95%.

Inception V3 model's features are combined with the other models in a hierarchical way. Firstly, high-level feature extraction is done from colonoscopy images using Inception v3. The extracted features are the fed as input to the ML algorithms. The individual predictions from these models are then evaluated using the majority voting technique so as to obtain the final classification. The integration of models is smoothed using a TensorFlow-based deep learning framework. Within this framework hyperparameter tuning and optimization techniques are incorporated for a seamless amalgamation of the different models.

V. Experimental Findings

A. Evaluation Results

Various evaluation metrics computed for the Colon Cancer Classification are Training Time (TT), Testing Time (TET), Area Under Curve (AUC), Classification Accuracy (CA), F1-Score, Precision, Recall, and Mathews Correlation Coefficient (MCC) [29–31]. Results for CC classification obtained are depicted in Table 1.

Analysing the three models suggest that NN is better than GB and DT. AUC, CA, F1-Score, Precision, Recall, and MCC statistics are highest for NN. For DT, the TT and TET are good, but still, if the results are good for all the other parameters, then the time factor is not that crucial. Seeing the results, it can be said that a combination of Inception V3 and NN proves to be the best model for Colon Cancer Classification.

B. Comparative Analysis

Comparative Analysis of CA w.r.t. former methods are depicted in Table 2. This shows that the model is quite efficient in its performance for CC Classification. The percentage improvement formula of CA is given in Eq. (1).

A 98.8% classification accuracy shows a significant improvement in comparison to existing methods. A 10.93% improvement is observed when compared with ANN. With BPNN model there is an improvement of 6.88%. With CNN the percentage increase in accuracy is 7.89%. Integrating Inception v3 with a Neural Network enhances feature extraction and model learning which makes the model more robust by capturing complex patterns in the medical images. With such high accuracy, pathologists can give accurate predictions aiding in early diagnosis.

$$\% \text{ Improvement} = (\text{Inc.} / \text{Org. CA}) \times 100 \quad (1)$$

Comparative Analysis of Precision w.r.t. former methods are depicted in Table 3. This shows that the model is quite efficient in precision. The percentage improvement formula for Precision is given in Eq. (2).

$$\% \text{ Improvement} = (\text{Inc.} / \text{Org. Precision}) \times 100 \quad (2)$$

Classification accuracy performance comparison shows a maximum of 10.93% increase in CA, as shown in Fig. 6. Precision performance comparison shows a maximum of 11.94% increase in Precision, as shown in Fig. 7.

Table 1. Results for colon cancer classification

Model	TT (s)	TET (s)	AUC	CA	F1	Precision	Recall	MCC
Neural Network (NN)	10.005	5.844	0.999	0.988	0.988	0.988	0.988	0.976
Gradient Boosting (GB)	37.224	2.848	0.933	0.903	0.903	0.903	0.903	0.806
Decision Tree (DT)	1.793	0.016	0.899	0.897	0.897	0.898	0.897	0.795

Table 2. Comparative Analysis of CA w.r.t. former methods

Model	CA	% Inc.
ANN	0.88 [32]	10.93
BPNN	0.92 [32]	6.88
CNN	0.91[32]	7.89
Our Approach (Inception v3 + NN)	0.988	-

Table 3. Comparative analysis of Precision w.r.t. former methods

Model	Precision	% Inc.
ANN	0.87 [32]	11.94
BPNN	0.91 [32]	7.89
CNN	0.92[32]	6.88
Our Approach (Inception v3 + NN)	0.988	-

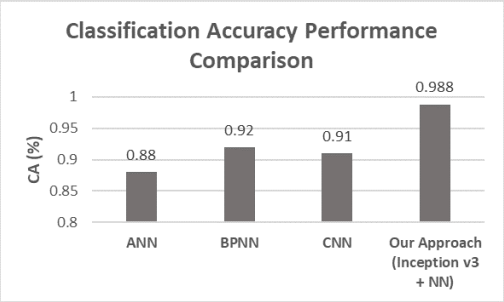


Fig. 6. Classification accuracy performance comparison.

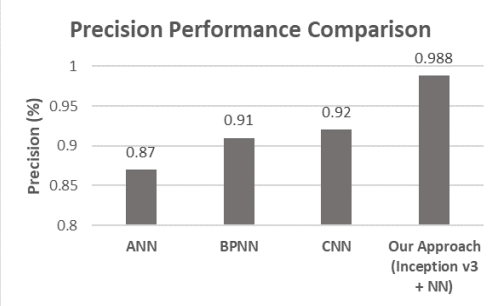


Fig. 7. Precision performance comparison.

C. Confusion Matrix (CM)

CM is a nxn matrix with True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values. Diagonal values moving from the top left to the bottom right give the count of total values that are predicted correctly [32–35]. Similarly, diagonal values moving from bottom left to top right give the count of total values that are predicted incorrectly. CM is identified for NN, GB, and DT. CM for NN is shown in Fig. 8, (335+342) gives a total count value of 672, which shows the correct predictions. Similarly, the same Fig. 8 (3+5) gives a total count value of 8 which shows the incorrect predictions.

Actual \ Predicted	colon_aca	colon_n	Σ
colon_aca	335	5	340
colon_n	3	337	340
Σ	338	342	680

Fig. 8. Confusion Matrix for Neural Network (NN).

CM for GB is shown in Fig. 9, (310+304) gives a total count value of 614, which shows the correct predictions. Similarly, the same Fig. 9 (30+36) gives a total count value of 66 which shows the incorrect predictions.

Actual \ Predicted	colon_aca	colon_n	Σ
colon_aca	310	30	340
colon_n	36	304	340
Σ	346	334	680

Fig. 9. Confusion Matrix for Gradient Boosting (GB).

CM for DT is shown in Fig. 10, (313+297) gives a total count value of 610, which shows the correct predictions. Similarly, the same Fig. 10 (43+27) gives a total count value of 70 which shows the incorrect predictions.

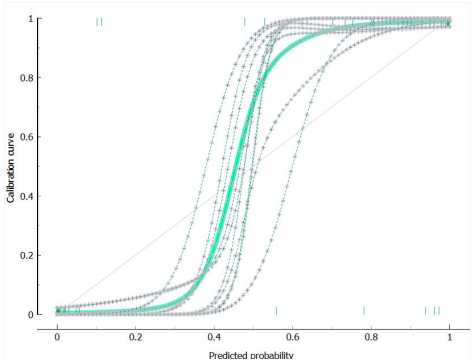
Actual \ Predicted	colon_aca	colon_n	Σ
colon_aca	313	27	340
colon_n	43	297	340
Σ	356	324	680

Fig. 10. Confusion Matrix for Decision Tree.

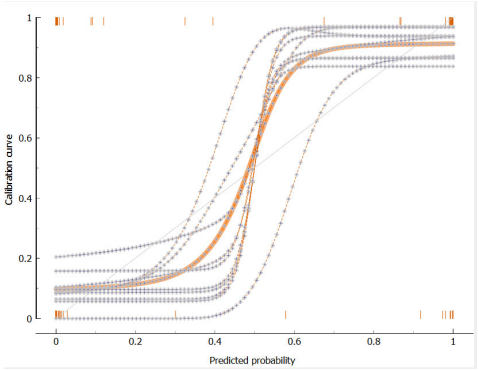
Seeing all the CM, one can find that NN outperforms the other two models, i.e., GB and DT in terms of correct predictions.

D. Calibration Plots (CP)

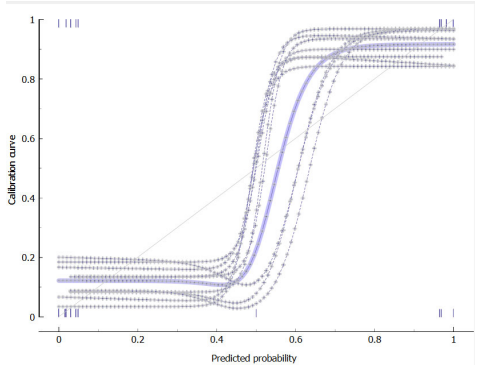
CP visualizes the relationship between predicted probabilities and actual outcomes. A well-developed model has an ideal diagonal line. Any line above the diagonal shows the over-confidence of the model in prediction. Any line below the diagonal shows the under-confidence of the model in prediction. In Fig. 11, we see the CP for Neural Network, Gradient Boosting & Decision Tree. Seeing the plots, it is clearly visible that NN has the best possible association w.r.t. the diagonal line in comparison to Gradient Boosting and Decision Tree.



a) Calibration Curve for Neural Network



b) Calibration Curve for Gradient Boosting

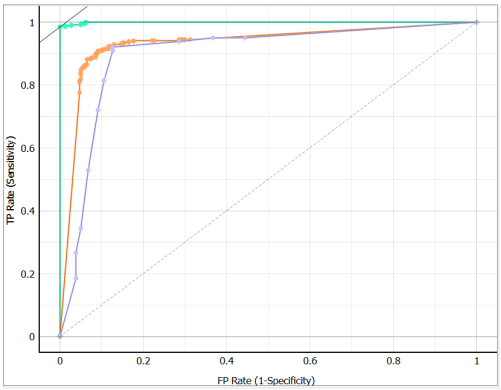


c) Calibration Curve for Decision Tree

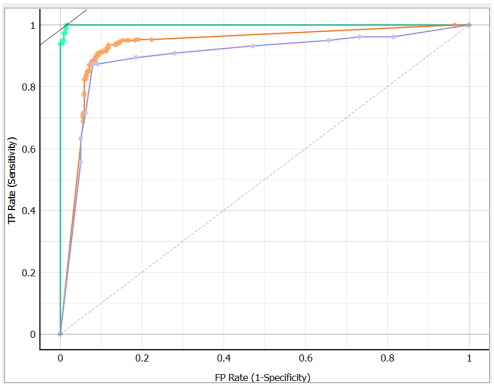
Fig. 11. Calibration Curves for Neural Network, Gradient Boosting & Decision Tree.

E. Receiver Operating Characteristic (ROC) Analysis

ROC analysis is a significant tool that is castoff to estimate the CC classification. It measures how well the model can differentiate between +ve and –ve cases. Sensitivity and Specificity are compared for both Colon Adenocarcinoma and Colon Benign cases as shown in Fig. 12. ROC curve plots the TP Rate on the y-axis in contrast to the FP Rate on the x-axis. The most suitable output lies near the topmost y-axis. In both the graphs, we could see that NN passes both GB and DT and thus has proved to be the most appropriate model for CC classification.



a) FP Rate vs TP Rate for colon_aca



b) FP Rate vs TP Rate for colon_n

Fig. 12. FP vs TP Rate for Colon Cancer Classes.

The rationale behind combining Inception v3 with Neural network is to strengthen both deep learning and traditional machine learning by taking advantage of ensemble learning to improve early colon cancer detection. Inception v3 outrivals in feature extraction and identifying complex patterns from Histopathological Images due to their hierarchical architecture and attention mechanisms. On the other hand, classification tasks are well handled by Neural Networks due to its ability to learn nonlinear relationships and handle high-dimensional data. Together these two models create an ensemble to improve the overall model performance, enhance generalization, reduce overfitting, and provide a more inclusive approach to early cancer detection.

Medical experts play a vital role in validating AI models and ensuring clinical standards. They ensure the correctness and significance of AI predictions by positioning them with clinical standards and real-world scenarios. Their participation is indispensable for regulatory compliance and addressing ethical considerations. Experts can give critical feedback by which AI models can be refined, the performance of models be enhanced and can integrate seamlessly into the existing clinical practices. Their commendation nurtures conviction and confirms that AI tools are dependable and operative in supporting accurate diagnoses and patient care. Teaming up with medical experts bridges the gap between technology and practical clinical application.

VI. Conclusion

In this work, we have automated the Colon Cancer Classification process by integrating deep learning and machine learning. The chief significance of integrating models is to take advantage of the best features that each model has to offer. A dataset of 200 Histopathological images is considered for experimental purposes. Two categories of colon conditions are identified in this research which include Colon Adenocarcinoma, which is a type of malignant colon cancer, and benign colon conditions. Inception v3 Model (IV3M), Neural Network, Gradient Boosting, Decision Tree, are unified in this work. For majoring in Colon Cancer Classification combination of IV3M, and Neural Network are giving better results. The experimental outcomes obtained through evaluation parameters, confusion matrix, calibration plots, and ROC analysis validate the accurate performance of the integrated approach. The research work will prove to be useful for individuals suffering from colon cancer and for the healthcare sector.

Conflict of Interest

The authors declare no conflict of interest.

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