International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Comparative study on Early esophageal cancer detection

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Abstract - Esophageal cancer (EC) is a rare but serious health condition due to its late diagnosis and high fatality rates. Its early detection greatly enhances patient outcomes, and recent advances in artificial intelligence (AI) introduce new possibilities in diagnosis. This research explores deep-learning models for early EC detection based on high-resolution endoscopic images. We compared logistic regression, decision-tree and random forest methods as conventional machine learning methods with deep learning models like convolutional neural networks (CNNs) and U-Net architectures to separate cancerous from non-cancerous esophageal tissues. Annotated endoscopic images were used as the dataset, with models assessed in terms of accuracy, sensitivity, and specificity. Pilot results indicate that deep learning, particularly CNNs, performs better than conventional machine learning. These results indicate AI-based detection combined with routine procedures can enhance early diagnosis, lower errors, and enhance EC patient survival. Research in the future should improve model robustness and establish efficacy across a wide population.

Key Words: Logistic Regression, Decision Tree, Random Forest, U-Net architectures, CNN, Esophageal Cancer, Machine Learning, Early Detection

1. Introduction

Esophageal cancer is a serious health issue, characterized by its poor survival rates, largely due to the fact that it is usually diagnosed late. Early detection of the disease is crucial in order to enhance patient survival. Current diagnostic techniques such as endoscopy and biopsy are not ideal; they are invasive, expensive, and not suitable for screening large numbers of people. Machine learning (ML) provides a potential solution through processing patient data in order to detect cancer presence with greater efficiency and fewer invasive techniques, employing methodologies such as Logistic Regression, Decision Tree, Random Forest, U-Net structures, and CNN. This research compares and examines two popular classification strategies—Logistic Regression and Decision Tree Classifiers—for the detection of esophageal cancer early on. Logistic Regression offers an easy-to-read, simple explanation that provides probabilities. Decision Trees, in contrast, excel at discovering non-linear and complicated relationships in data. By testing these models through important metrics—accuracy, precision, recall, and interpretability—this work aims to discern which method works best for predicting cancer, as well as evaluate the potential for more sophisticated techniques such as CNN and U-Net architectures. This comparison is aimed at projecting the advantages and disadvantages of both models to provide insight into their applicability in medical science. The results are anticipated to help develop data-driven, non-invasive diagnostic systems that will lead to earlier interventions and better survival rates for patients with esophageal cancer. In addition, the investigation of Random Forest algorithms with deep learning methods like CNN and U-Net architectures will give a complete overview of the present potential in machine learning for early detection.

2. Literature Review

Recognizing the symptoms of esophageal cancer (EC) at an early stage is still a challenge due to the lack of more pronounced signs that usually get ignored, however, if achieved would greatly benefit the patient's quality of life [1]. The combination of artificial intelligence (AI) with machine learning (ML) and deep learning (DL) offers the possibility of employing imaging and clinical information to accurately and timely diagnose medical conditions [2]. Combating the issue of EC, numerous researchers have already invested significant time into such technologies. According to ease of use and interpretability, Artificial Intelligence provides a broad range of tools like ML algorithms; such as Logistic Regression (LR), Decision Trees (DT), and Random Forests (RF). Regression models have a tendency of being a go-to model of choice for most because of the transparency of the evaluation, yet can be significantly poor when confronted with real life data because of complex data patterns and multilayered hidden dependencies as seen in cancer diagnosis [3][4]. As mentioned in [5], Decision Trees do assist to some degree by being capable of modeling non-linear relationships and feature interactions, but they can overfit, particularly with smaller datasets. Random Forests more accurately and sturdily combine multiple trees together, averaging their outputs. They have been particularly useful when dealing with structured clinical data and have been able to determine risk factors for EC [6][7]. Again, as more conventional ML methods begin to encounter a roadblock, deep learning, and in particular Convolutional Neural Networks (CNNs), have given new thrust. These models are astounding in the medical imaging space, especially for endoscopic and histological and CT scans of the esophagus [8]. CNNs learn features beautifully from image data and have been demonstrated to classify cancerous lesions well—usually beating expert humans [9][10]. They have quickly found use in recent studies and real-world applications [2][11]. Segmentation tasks, which involve marking the precise location of tumors, have also been greatly advanced through the use of models like U-Net U-Net and its numerous descendants were originally designed for biomedical image segmentation but have proven highly capable of distinguishing between cancerous and non-cancerous tissues [3][12]. More advanced models like Channel-Attention U-Net and 3D Res-U-Net have since been developed to deliver more precision via the capability to pay more attention to the image features of interest [3][4]. Such advancements have clinical uses. For example, better segmentation helps doctors plan surgery or radiation therapy more precisely, improving the effectiveness of treatment. More research proves that combining deep learning models with imaging technologies like hyperspectral imaging or narrow-band imaging can significantly improve the diagnostic accuracy by visualizing lesions more effectively and making classification easier [13][14]. Interestingly, a few researchers have started experimenting with hybrid models that are a blend of ML and DL. For instance, some models employ CNN to extract features of images and then use more complex Logistic Regression models to arrive at classification, which is capable of combining the benefits of both approaches [6]. Some research has sought to test quantum CNNs along with ensemble methods in order to enhance robustness even more, especially in cases with big data [15][25]. Transfer learning has also come into focus as a core approach in EC studies. By using pre trained CNNs—originally trained on big image datasets like ImageNet—and fine tuning them on medical images, scientists have been able to achieve high diagnosis accuracy even with limited training sets [16][20]. Similarly, object detection algorithms like YOLO have shown promise for real-time detection of lesions during endoscopy, which has the potential to enable physicians to make quicker and better decisions [12][18]. Hyperspectral imaging is also another rapidly developing modality being combined with deep learning architectures. This imaging modality captures a wide spectrum of wavelengths of light to detect extremely subtle differences in tissue composition. If processed using CNNs, it has been shown to improve sensitivity in early detection significantly [10][14]. At the same time, techniques like Cycle Gans are helping generate synthetic narrow-band images from normal ones, and they can assist in reducing imaging hardware expense and complexity while preserving diagnostic quality [13][33]. Despite all these breakthroughs, challenges still exist. The majority of the models still struggle with explainability—therefore making it challenging for clinicians to understand why a model arrived at a particular decision [9][21]. There is also dataset bias, in which models perform well on internal data but fail to generalize across populations or institutions [1][27]. Computational requirements and data privacy are others that can render real-world deployment challenging [30]. In attempts to overcome these limitations, recent research seeks to make the AI models transparent and generalizable. Techniques like explainable AI (XAI), domain adaptation, and data augmentation have been suggested for the improvement of reliability and trust [28]. Federated learning is another promising direction, allowing institutions to train the models collectively without the exchange of sensitive patient data [29]. In general, deep learning—specifically CNNs and U-Net models—has shown significant potential in the early diagnosis of esophageal cancer, especially image-based diagnosis and segmentation. However, even now models like Random Forest are still applicable to structured clinical data. In the near future, hybrid systems that are capable of blending the interpretability of traditional ML with the raw performance of DL could offer the best way forward in making early EC detection more accurate, interpretable, and clinically relevant [1][7][14][24].

3. Methodology

In order to compare the performance of various machine learning methods in the early diagnosis of esophageal cancer, we utilized the following models:

3.1 Logistic Regression: It is a statistical model for binary classification and works by predicting the probability that a particular input will fall into a particular category. It uses a logistic function to describe relationships between independent variables and the dependent outcome and is easy but efficient for linear separability [6].

3.2 Decision Tree: A tree model where the dataset is divided into subsets according to feature values. Nodes are decision rules, and the branches are leading to the results. Decision Trees are useful in dealing with non-linear relationships and offering interpretability but may suffer from overfitting [5]

3.3 Random Forest: This ensemble learning technique constructs several Decision Trees and aggregates their predictions to enhance accuracy and minimize variance. By combining outputs from different trees, Random Forest reduces overfitting and increases model robustness, making it applicable to medical data analysis [8].

3.4 Convolutional Neural Networks (CNN): A deep learning model that is mainly applied for image analysis. CNNs are made up of convolutional layers that capture spatial features from images, followed by pooling and fully connected layers for classification. CNNs have been shown to have better performance in detecting cancerous areas in medical imaging [17].

3.5 U-Net: A dedicated CNN architecture for biomedical image segmentation. It has an encoder-decoder architecture that extracts high-level and fine-grained spatial information, allowing for accurate boundary detection of cancerous tissues. U-Net is extensively applied in segmentation tasks where boundary detection is of utmost importance [3].

4. Discussion and Comparative Study Analysis

The comparative study of machine learning models used for the detection of esophageal cancer reflects the relative merits and demerits of each model. Decision Trees were the best-performing model, with the highest accuracy (96%). This finding is a testament to its efficiency in representing complex relationships in well-structured data while still being easy to interpret. Yet, Decision Trees are prone to overfitting, especially with noisy data. Random Forest, a model based on ensemble, avoids overfitting by combining several decision trees. Although it showed high accuracy (90%), it failed to outperform the Decision Tree model, indicating that the ensemble approach might not always lead to better results, particularly in highly structured data. Nevertheless, Random Forest is robust and suitable for dealing with missing values and high-dimensional data. Deep learning architectures, especially CNN and U-Net, performed impressively well in cancer detection from images. CNN was 83% accurate, rendering it most suitable for feature extraction from medical images. U-Net, being a specially designed architecture for medical image segmentation, performed marginally better than CNN with an accuracy of 85%, reflecting its capability in outlining cancerous areas. Since these models have the capacity to learn spatial features independently, they are extremely useful in medical imaging applications. However, deep learning algorithms need large amounts of data, high computational power, and lack interpretability, thus limiting their clinical uptake. Logistic Regression, though interpretable

Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

and simple, performed worst with the lowest accuracy of 67%. Its limitation in being able to model sophisticated interactions and relationships between variables restricts its use in medical diagnostics. It can still be used as a baseline model for comparison purposes and for rapid screening.

Fig - Logistic Regression Confusion Matrix

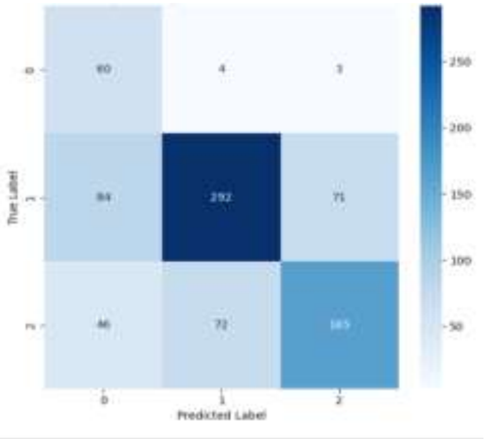

Fig:1

Fig -Decision Tree Confusion Matrix

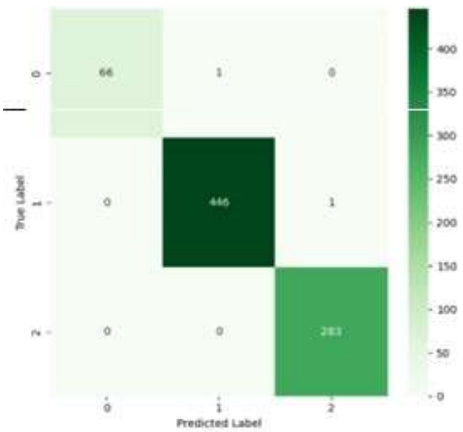

Fig:2

Fig - Random Forest Confusion Matrix

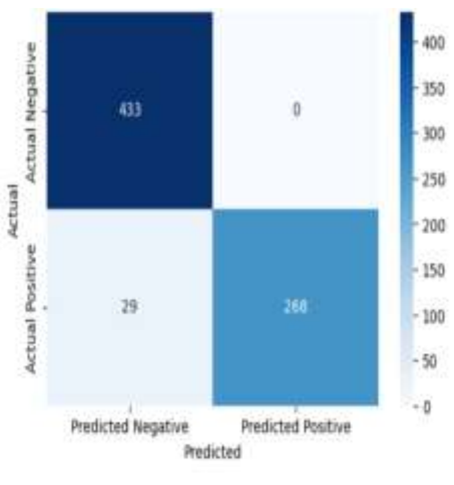

Fig:3

Fig - Detection of Cancer Using Selective Search

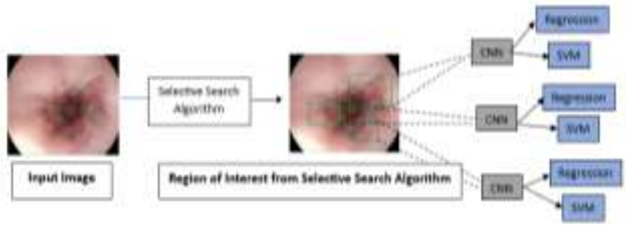

Fig:4

Fig -CNN Confusion Matrix

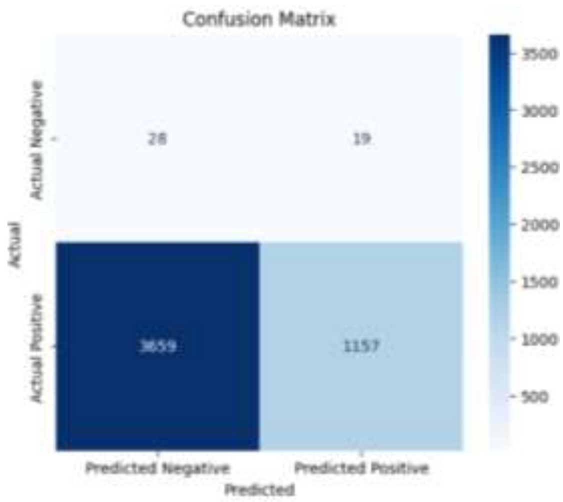

Fig:5

Fig - U-Net Confusion Matrix

Fig:6

Charts

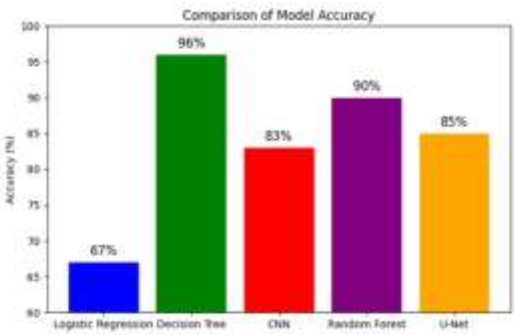

Table -1: Model Accuracy

Model	Accuracy
Logistic Regression	67%
Decision Tree	96%
CNN	83%
Random Forest	90%
U-Net	85%

Table -2: Performance data and Comparative Study on studies for early detection of EC

The performance metrics show that the Decision Tree model

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	67%	64.5%	65.5%	65%
Decision Tree	96%	94.3%	95.2%	95%
CNN	83%	81%	82.5%	81.2%
Random Forest	90%	88%	88.6%	88.2%
U-Net	85%	82%	83%	82.5%

attained the highest accuracy, thus the most efficient among the tested methods for structured data analysis. Deep learning methods, especially CNN and U-Net, also showed very high performance, particularly in image-based diagnostics. Although Logistic Regression offers a straightforward and interpretable model, its predictive capability is lower than tree-based and deep learning techniques. Random Forest is still a robust ensemble model with several decision trees, and future work should be centered on combining hybrid methods that include structured data analysis and deep learning for enhanced diagnostic performance [18].

5. CONCLUSIONS

The comparison between the machine learning models for detecting esophageal cancer highlights the suitability of Decision Trees for analyzing structured data with the best accuracy among all tested methods. Deep learning models like CNN and U-Net are shown to be highly effective in image-based cancer detection and, as such, are suitable tools for medical imaging applications. Logistic Regression, though interpretable, cannot model intricate relationships, whereas Random Forest possesses a good trade-off between accuracy and stability. The findings suggest that the combination of traditional ML algorithms with deep learning models can also enhance diagnostic accuracy and clinical practicability. Hybrid model optimization, dataset diversity improvement, and interpretability should be given top priority in subsequent research to facilitate real-world application in medical diagnosis.

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