*Bahrain Medical Bulletin, Vol. 48, No. 2, June 2026*

# Lung Cancer Classification Using Hybrid Machine Learning Algorithm

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## ABSTRACT

**Automated classification of lung cancer using chest CT scans is an important topic, which serves as a support tool for doctors, and the more efficient these systems are, the more effective they will be in saving people's lives. This research aims to design a hybrid classification model for lung cancer types based on the Chest CT Scan model, where the EfficientNet-B3 model is Fine-tuned to extract features from images, a machine learning model is used to make the classification decision, and to ensure the effectiveness of the machine learning model, its hyperparameters are optimized using Bayes Optimizer. An accuracy of 95.34%, sensitivity of 95%, recall of 97%, and F1-score of 96% were achieved on the Chest CT-Scan images Dataset using the proposed model.**

***Keywords: Lung Cancer, EfficientNet, Machine Learning, Chest CT-Scans, Hybrid Model, Bayesian Optimizer.***

## INTRODUCTION

Cancer, especially lung cancer, is one of the deadliest diseases in the world, with an estimated 1.8 million deaths from lung cancer in 2020 alone[1,2] and an estimated 2.2 million cases in the same year[3], The reason for the high number of deaths is due to delayed diagnosis, while early diagnosis helps save patients[4]. Automated diagnosis systems have emerged as an assistant solution for doctors, and in recent years we have noticed the remarkable development of artificial intelligence systems in all areas of life and have become heavily relied upon even in the medical field[5], but in order to be used effectively, they must have very high performance and reliability due to the sensitivity of this field[6], and therefore improving the accuracy of early automated diagnosis of lung cancer contributes greatly to saving people's lives.

In recent years, many automated systems have emerged to detect diseases from medical images, which rely on machine learning, deep learning and hybrids[7]. However, some of these systems lack sufficient accuracy and others consume a lot of computational resources due to the use of high-resolution images with hybrid models or very complex deep learning models[8]. Therefore, in this research, we propose a hybrid recognition system that uses the power of the EfficientNet model for its strength in extracting features, with machine learning models such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Logistic Regression (LR), or Extra Trees (ET) for their high decision-making capabilities, ease of adjustment, and low computational and time costs.

By integrating the power of the EfficientNet-B3 model in feature extraction, the power of ML in decision making, scaling images to medium size and using a medium-sized version of the EfficientNet model, the proposed model gives high performance at a lower cost than the State of Art high-performance models.

## Literature Review

Given the importance of the topic of automatic cancer detection, especially lung cancer, which is one of the deadliest types in the world, this topic has received the attention of many researchers, such as[9], where the researchers conducted a study in which a deep learning model was proposed and compared with several pre-trained models (ResNet-50, Inception V3, and Xception) to detect and Classify lung cancer. The proposed model, which consists of three convolutional layers interspersed with three max-pooling layers followed by a flatten layer and 4 fully connected layers, achieved an accuracy of 92%, while ResNet-50, Inception V3, and Xception achieved accuracy of 84.13%, 82.07%, and 82.1% respectively on Chest CT-Scan images Dataset.

While converted the Chest CT-Scan images Dataset from a multi-class dataset to a two-class dataset, by grouping the infected the total number of images in the proposed dataset reached 15,000 cases into one class, and they achieved F1-score of 98.4% using Enhanced CNN[10]. Proposed a CNN model, resizing images to 385x385 pixels, and achieving 94% accuracy on the same dataset[11]. Merged CT-scans from the LUNA16, LIDIC-IDRI and Chest CT-scans datasets, and augmented the resulting dataset so that. Using transfer learning with the MobileNetV2 model, the researchers were able to achieve 98% accuracy in classifying images into normal and abnormal[12].

## Proposed Methodology

The proposed methodology includes several stages, and Figure (1) shows the block diagram of the framework.

### Dataset:

The dataset "Chest CT-Scan images Dataset"[13] is used in this research, which contains 1000 Chest CT-Scan images divided into 613 images as training set, 315 images as test set, and 72 images as validation set. The images in the dataset fall into four classes:

- Adenocarcinoma: labeled as 0.
- Large cell carcinoma: labeled as 1.
- Normal: labeled as 2.
- Squamous cell carcinoma: labeled as 3.

Preprocessing: At this stage, the images in the dataset are read, resized to a size of 300*300 pixels, and then scaled to grayscale images in the range from 0 to 1.

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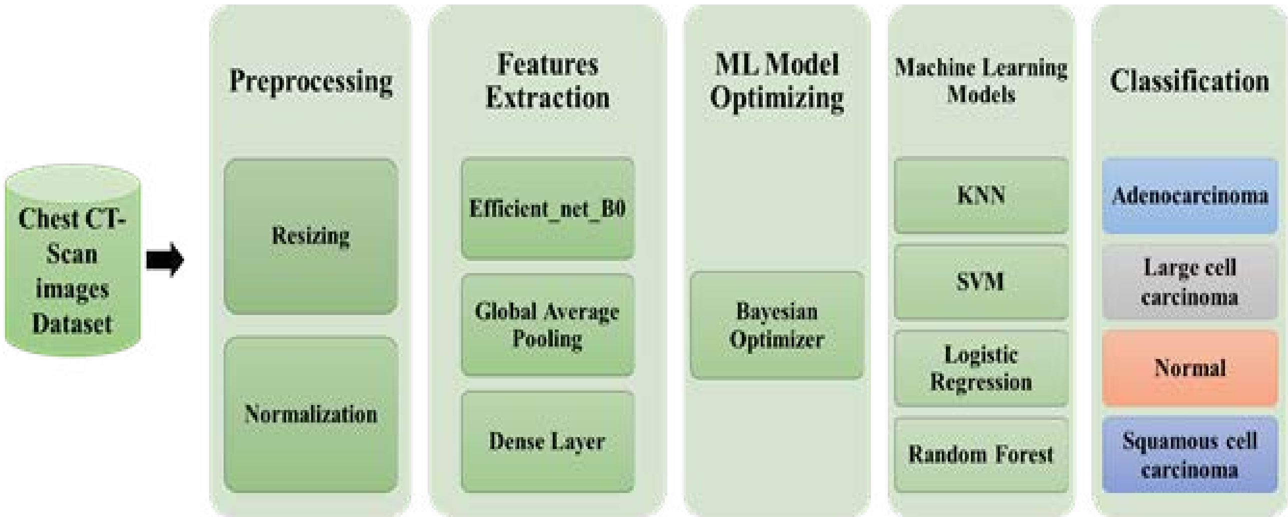


**Figure 1.** The Proposed Methodology Framework

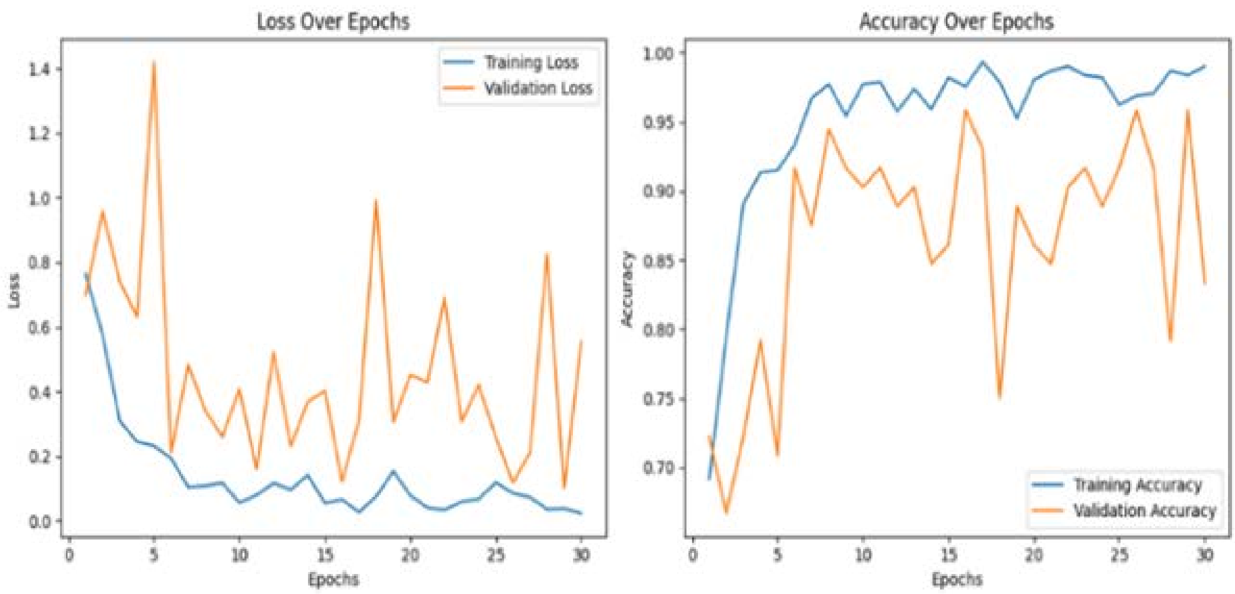


**Figure 2.** Efficientnet-B3 Training Curves

**Preprocessing:** The EfficientNet is a high-performance model, that requires low-computational resource compared to its counterparts, as it works to scale width, resolution and depth in a uniform manner for modeling. EfficientNet-B3 model, a member of EfficientNet family, balances performance and computational resources efficiency, making it suitable for medical image analysis and feature extraction.

### Machine learning model optimizing:

To achieve best performance using machine learning models, their hyperparameters must be fine-tuned using the training set. For this purpose, we employ Bayesian Optimizer (Table 1).

Bayesian optimization works by creating a probabilistic model of the objective function and choosing the next evaluation point using a gain function, which works according to the formula (1):

$$x_{next} = \underset{x \in X}{\operatorname{argmax}} \propto (x|D) \tag{1}$$

$x_{next}$: the next point to evaluate.

$X$: the hyperparameters search space.

$\propto (x|D)$: the acquisition function which guides the search based on the data $D$.

## RESULTS

The EfficientNet-B3 model is used to extract features, but before using this model, additional layers must be trained on the research data set, while freezing the other layers. AdamW Optimizer is used to perform strong generalization, and the learning rate is (1e-3). The table (2) shows the parameters and layers of the proposed model.

We use an adaptive average layer, to reduce the spatial dimensions of the output of the model, followed by a flattening layer to convert the output of the previous layer into a vector, and then a density layer consisting of neurons to make the classification decision. Table (3) shows the parameters and size of the proposed model.

**Table 1.** The Range of Values and the Best Value for Ml Model Hyperparameters

| Model | Search Space | Best Hyper Parameter |
|---|---|---|
| **ET** | n_estimators: [50, 300] | 153 |
| **LR** | C: [0.01, 10] | 'C'= 0.16994636371262764<br>'log-uniform' |
| **KNN** | num_neighbors: [1, 20] | 9 |
| **SVM** | "C": [0.1, 10] | 'C'= 0.661009829541915<br>'log-uniform' |

**Table 2.** Efficientnet-B3 Layers Summary

| Layer | Type | Output Shape | Parameters |
|---|---|---|---|
| Input Layer | Input (3, 300, 300) | (8, 3, 300, 300) | - |
| Conv2D | Conv2d (3, 40, kernel=3x3) | (8, 40, 150, 150) | 1,080 |
| BatchNorm2D | BatchNorm2d (40) | (8, 40, 150, 150) | 80 |
| SiLU | SiLU (Swish Activation) | (8, 40, 150, 150) | 0 |
| MBConv1 | MBConv (40 → 24) | (8, 24, 150, 150) | 5,456 |
| MBConv2 | MBConv (24 → 32) | (8, 32, 75, 75) | 10,900 |
| MBConv3 | MBConv (32 → 48) | (8, 48, 75, 75) | 20,064 |
| MBConv4 | MBConv (48 → 96) | (8, 96, 38, 38) | 43,776 |
| MBConv5 | MBConv (96 → 136) | (8, 136, 19, 19) | 84,480 |
| MBConv6 | MBConv (136 → 232) | (8, 232, 19, 19) | 161,232 |
| MBConv7 | MBConv (232 → 384) | (8, 384, 10, 10) | 352,512 |
| Conv2D | Conv2d (384, 1536, 1x1) | (8, 1536, 10, 10) | 590,592 |
| BatchNorm2D | BatchNorm2d (1536) | (8, 1536, 10, 10) | 3,072 |
| SiLU | SiLU (Swish Activation) | (8, 1536, 10, 10) | 0 |
| Adaptive Pooling | AdaptiveAvgPool2d (1x1) | (8, 1536, 1, 1) | 0 |
| Flatten | Flatten () | (8, 1536) | 0 |
| Fully Connected | Linear (1536 → 4) | (8, 4) | 6,148 |

**Table 3.** Efficientnet-B3 Parameters

| Category | Total Parameters |
|---|---|
| Trainable | 6,148 |
| Non-Trainable (Frozen) | 10,688,122 |
| Total | 10,694,270 |

**Table 4.** The Proposed Models Results

| Model | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| EfficientNet_B3 | 0.93 | 0.95 | 0.94 | 0.9333 |
| EfficientNet_B3+Extra Trees | 0.92 | 0.93 | 0.92 | 0.9175 |
| EfficientNet_B3+LR | 0.95 | 0.96 | 0.95 | 0.9492 |
| EfficientNet_B3+SVM | 0.95 | 0.97 | 0.96 | 0.9492 |
| EfficientNet_B3+KNN | 0.95 | 0.97 | 0.95 | 0.9524 |

**Table 5.** Comparison with State-Of-Art Studies

| Authors | Applied model | Classification Type | Dataset | Accuracy | F1-Score |
|---|---|---|---|---|---|
| (Mamun M. et al., 2023) | CNN | Multi-class | Chest CT-Scan images | 92% | NA |
| (Shatnawi et al., 2025) | Enhanced CNN | Binary | Chest CT-Scan images | 100% | 98.4% |
| (Shoaib et al.,2023) | CNN | Multi-class | Chest CT-Scan images | 94% | NA |
| (Alheeti et al., 2024) | CNN with transfer learning MobileNetV2 | Binary | Chest CT-Scan images + LDIC-IDRI + Luna16 | 98% | NA |
| Ours, 2025 | Hybrid | Multi-class | Chest CT-Scan images | 95.24% | 95% |

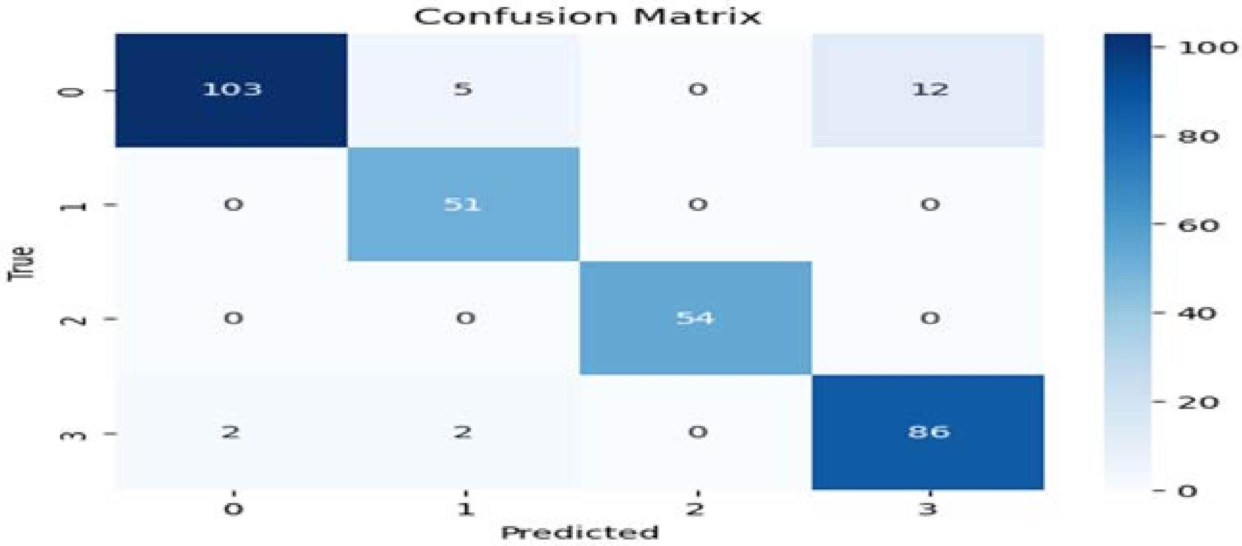


**Figure 3.** Efficientnet-B3 Confusion Matrix for Testing Set

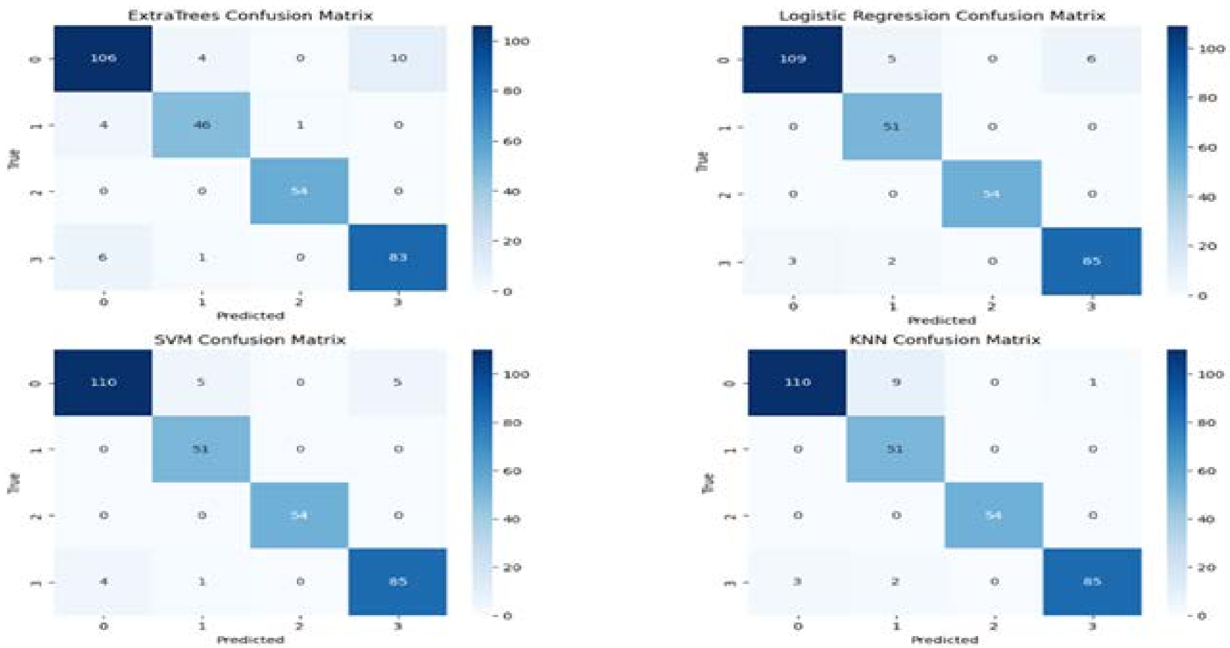


**Figure 4.** The Proposed Models Confusion Matrixes

Figure (2) shows that the model performed well after a few iterations, due to using EfficientNet-B3 model and freezing the trained layers, reaching an accuracy of 95.83% on the validation set, and 93.33% on the testing set. Figure (3) shows the confusion matrix for the used EfficientNet-B3 model.

Figure (3) shows that model EfficientNet-B3 misclassified 21 cases out of 315.

To improve performance, the output of the penultimate layer of the EfficientNet-B3 model is taken and passed through one of the proposed machines learning classifiers, using the Bayesian optimizer mentioned above, to obtain the confusion matrix for each model as shown in Figure (4).

Figure (4) shows that model EfficientNet-B3+ET misclassified 16, EfficientNet-B3+LR misclassified 26, EfficientNet-B3+SVM misclassified 15, and EfficientNet-B3+KNN misclassified 15 cases out of 315. Table (4) shows a comparison between the performance of EfficientNet-B3 in the traditional way and the performance of the proposed hybrid models using 4 different performance evaluation metrics.

The results in Table (4) show the effectiveness of the proposed model, using all performance evaluation metrics, as the EfficientNet_B3+KNN model reached the highest accuracy of 95.24%, outperforming the EfficientNet_B3+SVM model by 0.32% in terms of accuracy, but lower in terms of F1-score, which means that EfficientNet_B3+KNN will perform better with the major or most common classes, while EfficientNet_B3+SVM will perform better with the minor or less common classes.

Table (5) shows a comparison with state-of-art studies, in terms of accuracy and F1 score, number of classes and dataset used.

Table (5) shows that the model proposed in this study is better than all models previously proposed on the same dataset in the multi-class classification task, outperforming the best model[11] by 1.24% in terms of accuracy.

## CONCLUSION

**In this study, a hybrid classification model was designed to classify lung cancer types. By taking advantage of the power of the EfficientNet-B3 model in feature extraction and the power of machine learning models in decision making, high performance was achieved. The model's performance can also be improved by using higher resolution images with a higher version of the EfficientNet family and integrating more than one dataset, which increases the model's generalizability.**

**Despite the promising results, our study has limitations. Relying on a single dataset restricts generalizability; future work should validate the model on larger, more diverse datasets from multiple sources. Expanding the model for multi-class classification of cancer subtypes or disease staging is another direction. Addressing the computational cost of training deep models and enhancing model interpretability (e.g., using Grad-CAM) remain crucial for clinical adoption and future improvements.**

**Authorship Contribution:** All authors share equal effort contribution towards (1) substantial contributions to conception and design, acquisition, analysis and interpretation of data; (2) drafting the article and revising it critically for important intellectual content; and (3) final approval of the manuscript version to be published. Yes.

**Potential Conflicts of Interest:** None

**Competing Interest:** None

**Acceptance Date:** 21 October 2025

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