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Lung Cancer Detection by Hybrid Learning Method Applying SMOTE Technique

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Abstract

Lung cancer is a very deadly disease. However, early diagnosis and detection is an essential factor in overcoming this deadly disease. Tumors formed in this disease's initial stage are divided into benign and malignant. These can be visualized using a computed tomography (CT) scan. Thanks to machine learning and deep learning, cancer stages can be detected using these images. In our study, the best and most promising results in the literature were obtained by using a hybrid learning architecture. The data mining techniques we use in obtaining these results also play a significant role. The best accuracy result we obtained belongs to the CNN+GBC hybrid algorithm, which we recommend with 99.71%.

1. INTRODUCTION

Lung cancer is the most dangerous type of cancer among cancer types when its incidence and mortality rates are considered in humans [1]. According to the American Cancer Society, lung cancer is the second most common type of cancer in both sexes, after prostate and breast cancer [2]. Each year, human deaths from lung cancer are more than colon, breast, and prostate cancers combined [2]. According to The International Agency for Research on Cancer (IARC) data, the number of deaths from this disease reached 1.8 million people in 2020, which equals 18.0% of total cancer deaths compared to total cancer types [3]. Lung cancer is caused by the growth of tumors, with cells growing out of control. It makes it difficult for the patient to breathe. In lung cancer, the small cell type is called adenocarcin, squamous cell, while the large cell carcinoma is called [4, 5]. It has been observed that 80% of people who have died from lung cancer have used cigarettes and alcohol [6].

In lung cancer, as in every other disease, early detection and detection saves people from death. When researchers analyzed the statistics of the 8th Tumor, Node, Metastasis (TNM) staging system, it shows that early detection and detection reduces survival rates from as high as 92% for very early stage (T1a) lung cancer to 38-47% at T4 stage [7]. There are scanning methods such as computed tomography (CT), magnetic resonance imaging (MRI) and chest x-ray in diagnosing and detecting the disease.

With the advancement of imaging technologies, the use of devices that emit radiation at lower doses, thanks to scans such as low-dose computed tomography (LDCT), also results in a much higher number of people to be examined than those who are actually sick. In this case, it cannot meet the increasing demand since it significantly increases the workload on radiologists in detecting and diagnosing the disease of people with cancer. For this reason, 2%-4% of patients can be screened in the USA [8-10].

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These images are processed in effective artificial intelligence algorithms, providing great convenience to healthcare professionals in disease detection and diagnosis. Artificial intelligence technologies make training both in software and hardware an effective solution [9].

Thanks to the effective feature extraction and learning of convolutional neural networks, effective classifications, namely detection and diagnosis, can be made in lung cancer as well as in many diseases by using CNNs. Among these artificial intelligence technologies, machine learning, deep learning and their derivatives hybrids are used as software. Especially convolutional neural networks (CNN) are very effective in processing images and learning by extracting features from these images [11]. Employees of the world's leading artificial intelligence research companies are trained on LDCT volumes and work on cancer risk prediction with effective CNN models [8, 12]. Recently, many promising CNN models have been applied to disease diagnosis. Alakwaa et al. [13] detected lung cancer using CNN and 3D images. Welch et al. [14] used AlexNet for lung cancer classification.

The main purpose of these studies is to reach high-accuracy results in a short time in lung cancer images. For this purpose, AlexNet [15], VGG [16], DCNN [17] and DenseNet [18] models were used. In another study, it achieved an accuracy score of 97.27% using the AlexNet-based model and the LIDC-IDRI dataset [19]. In another study, lung cancer detection was performed using the segmentation method together with deep learning [20].

Considering the above studies, we come across many successful studies on the detection of lung cancer.

In this study, it is aimed to meet the increasing number of scans with high accuracy rates by using artificial intelligence.

The main contributions of this study can be summarized as follows.

- For the first time, hybrid learning method is applied to this dataset.
- It achieves the most successful result in the literature.

The next parts of the study are as follows. The second section is material and method, the third section is experimental results, and the last section is conclusion.

2. MATERIALS AND METHODS

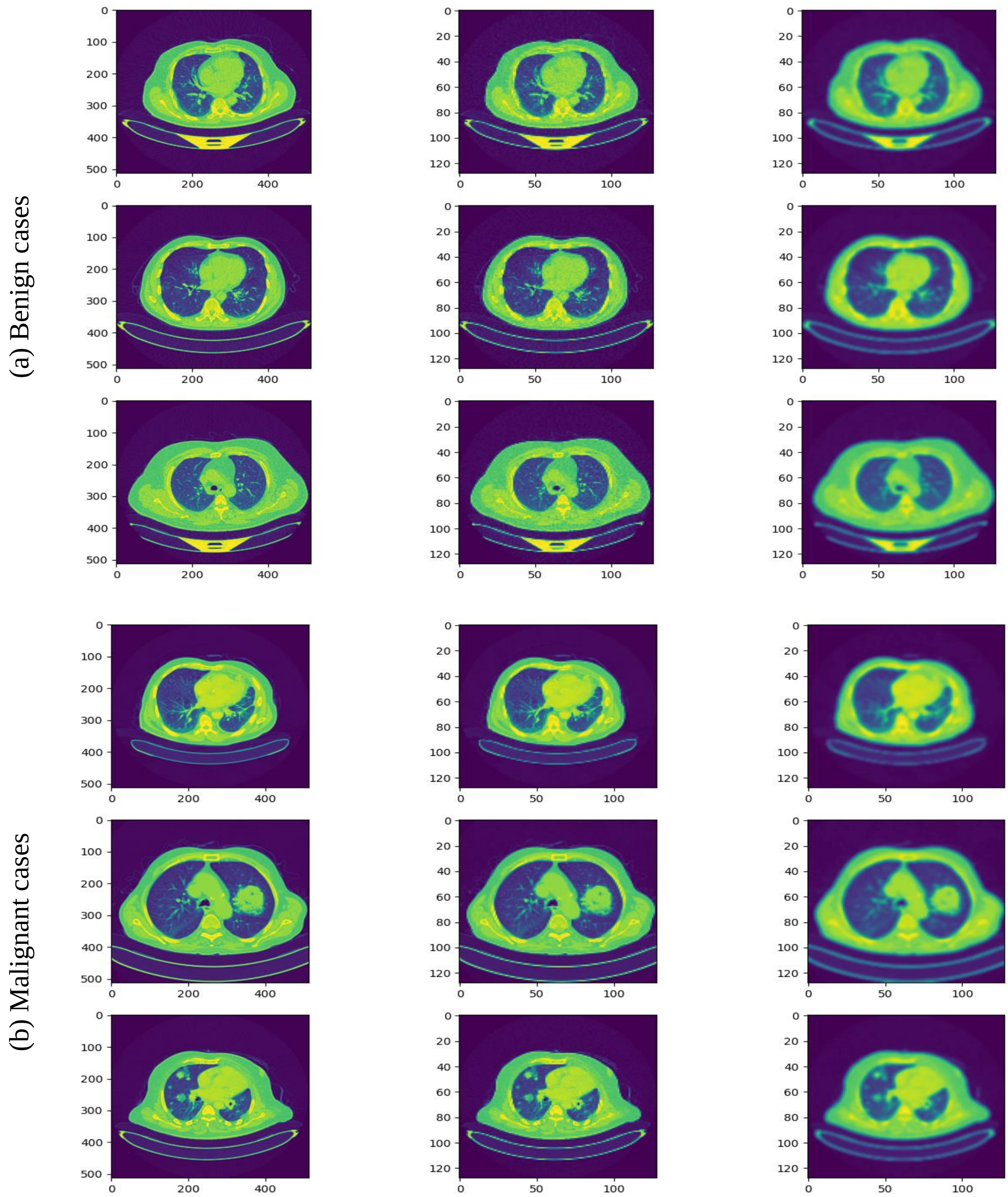
In this section, general information about the dataset and the techniques and algorithms used in the study will be mentioned.

2.1. Dataset

The dataset consisting of images of lung patients diagnosed with computed tomography (CT) was obtained in Iraq-Oncology Training Hospital/National Cancer Diseases Center (IQ-OTH/NCCD) [21] over a period of three months. Among the subjects that make up the dataset, there are images of healthy and cancer patients with different stages. 110 cases in the dataset are divided into 3 classes as normal, benign and malignant, and it consists of 1190 images in total. The number of malignant cases is 40, benign cases are 15 and the number of normal cases is 55.

110 cases participating in CT scans differ according to gender, age, education level, area of residence and living situation. As can be seen from the number of cases that make up the dataset, the dataset has an uneven distribution. The SMOTE technique, which we will explain below, has been applied to eliminate this problem.

Figure 1 shows some sections belonging to three classes from the dataset consisting of lung images.


(a) Benign cases
(b) Malignant cases

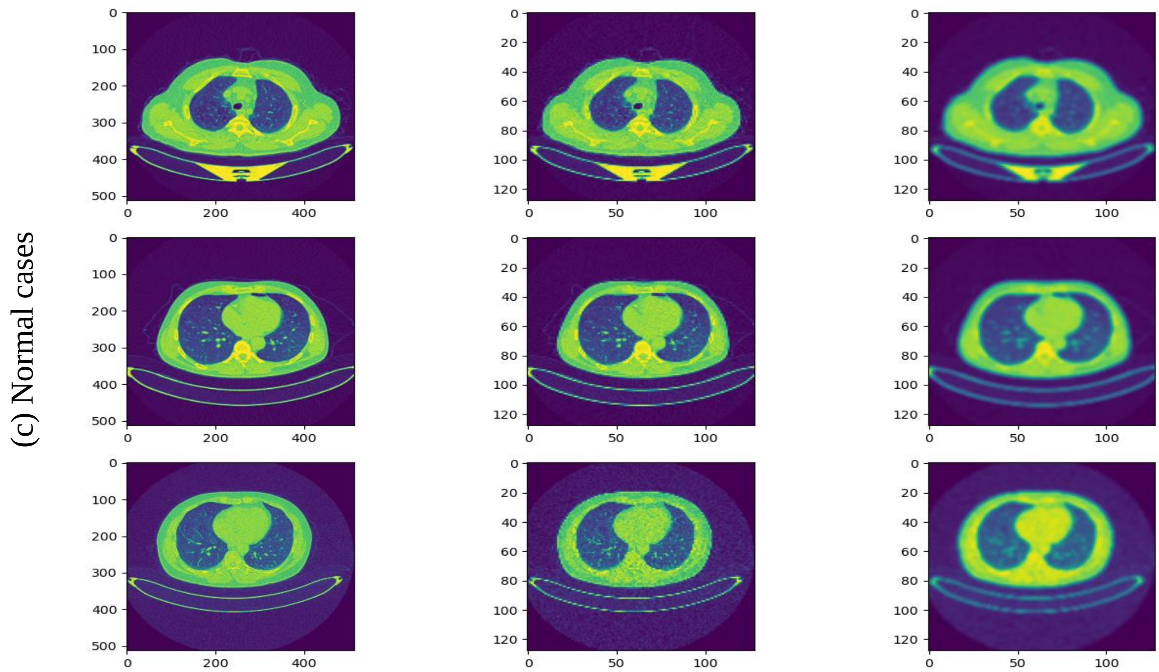


Figure 1. *Class status of lung images*

2.2. SMOTE

It is one of the effective methods used to stabilize an unbalanced data set. The Synthetic Minority Oversampling Technique, which tries to avoid the overfitting problem, is called SMOTE [22]. In this method, instead of multiplying the number of minority instances, it creates new instances of minority class synthetically by interpolating between instances of the minority class that are close to each other.

2.3. CNN Features Extraction and CNN Classification

Deep learning and CNN architectures, which are included in machine learning and have a wide area, are successfully used in feature extraction and classification. CNNs are especially effectively used to process visual data or images [23]. CNNs are used in this regard and as an excellent tool for image processing on the computer. To improve the performance of a CNN structure with low-value bit-width activation and low-precision weights, Zhuang et al. proposed a two-stage optimization technique [24]. In another study, they developed a GVCNN (group view convolutional neural network), a CNN network that can perform effectively in 3D shape recognition [25]. In addition to these studies, CNN architectures in an energy efficient reconfigurable accelerator [26], in image segmentation [27] and image fusion [28] is used. CNN architectures do relatively less preprocessing in feature extraction than other machine learning algorithms. In feature extraction, the process that is independent of human effort and prior knowledge is a great advantage and convenience.

CNNs are effectively used for feature extraction from images. In our study, we classify medical lung cancer images as multiple in both CNN architecture and classical machine learning models by using these features of CNNs. The CNN architectures we used for feature extraction are given in Table 1 and the CNN architectures we used for classification in Table 2.

Table 1. *CNN feature extraction architecture*

Type of Layers	*Type of Data*	*Dimension of Data*
Input layer	*Float 32*	*(None, 64, 64, 1)*
Conv2D	*Float 32*	*(None, 64, 64, 16)*
MaxPooling2D	*Float 32*	*(None, 32, 32, 16)*
BatchNormalization	*Float 32*	*(None, 32, 32, 16)*
Conv2D_1	*Float 32*	*(None, 30, 30, 32)*

Conv2D_2	*Float 32*	*(None, 28, 28, 64)*
MaxPooling2D_1	*Float 32*	*(None, 14, 14, 64)*
BatchNormalization_1	*Float 32*	*(None, 14, 14, 64)*
Conv2D_3	*Float 32*	*(None, 12, 12, 128)*
Conv2D_4	*Float 32*	*(None, 10, 10, 256)*
Flatten	*Float 32*	*(None, 25600)*
Dropout	*Float 32*	*(None, 25600)*
Dense	*Float 32*	*(None, 256)*
BatchNormalization_2	*Float 32*	*(None, 256)*
Dropout_1	*Float 32*	*(None, 256)*
Dense_1	*Float 32*	*(None, 128)*
BatchNormalization_3	*Float 32*	*(None, 128)*
Dense_2	*Float 32*	*(None, 64)*
BatchNormalization_4	*Float 32*	*(None, 64)*
Dropout_2	*Float 32*	*(None, 64)*
Dense_3	*Float 32*	*(None, 32)*
BatchNormalization_5	*Float 32*	*(None, 32)*
Dense_4	*Float 32*	*(None, 7)*

Table 2. *CNN classification architecture*

Type of Layers	Type of Data	Dimension of Data
Input layer	Float 32	(None, 64, 64, 1)
Conv2D	Float 32	(None, 64, 64, 16)
MaxPooling2D	Float 32	(None, 32, 32, 16)
BatchNormalization	Float 32	(None, 32, 32, 16)
Conv2D_1	Float 32	(None, 30, 30, 32)
Conv2D_2	Float 32	(None, 28, 28, 64)
MaxPooling2D_1	Float 32	(None, 14, 14, 64)
BatchNormalization_1	Float 32	(None, 14, 14, 64)
Conv2D_3	Float 32	(None, 12, 12, 128)
Conv2D_4	Float 32	(None, 10, 10, 256)
Flatten	Float 32	(None, 25600)
Dropout	Float 32	(None, 25600)
Dense	Float 32	(None, 256)
BatchNormalization_2	Float 32	(None, 256)
Dropout_1	Float 32	(None, 256)
Dense_1	Float 32	(None, 128)
BatchNormalization_3	Float 32	(None, 128)
Dense_2	Float 32	(None, 64)
BatchNormalization_4	Float 32	(None, 64)
Dropout_2	Float 32	(None, 64)

Dense_3	Float 32	(None, 32)
BatchNormalization_5	Float 32	(None, 32)
Dense_4	Float 32	(None, 7)
Dense_5	Float 32	(None, 128)
Dense_6	Float 32	(None, 1)

2.4. Machine Learning

Decision tree classifiers (DTCs) are used effectively in many different fields such as character recognition, medical diagnosis, radar signal classification and speech recognition. Perhaps the most important feature of DTCs is their ability to find solutions that are easier to segment and interpret, by making the complex decision-making process simpler. Considering the advantages of DTCs over single-state classifiers, it has come to the forefront among other machine learning algorithms thanks to its features such as decision and search strategies, tree structure design, and feature selection at each internal node [29].

Random forest can be defined as a classifier, an integrated learning mode that includes multiple decision trees. Each tree forming the random forest can be defined as a classifier that trains a randomly retrieved piece from the sample set. In this way, multitree classifiers form a specific training model classifier matrix. Finally, this integrated classifier, which consists of many classifier trees, can classify in the processed dataset thanks to the majority vote method [30].

The K-nearest neighbor (KNN) algorithm is one of the effective statistical and machine learning classification algorithms for pattern recognition. It is among the simplest learning algorithms [31]. The main idea of this algorithm is to classify an instance in the feature space and assign the instance to the class to which the majority of K instances are closest to the sample to be classified. Thanks to the selected neighbors, the sample can be correctly classified [32]. One disadvantage of KNN is that it requires very large amounts of computation in time.

Support vector machines (SVM) are a supervised machine learning algorithm for regression and classification. The feature of SVM is that it minimizes the empirical classification error and can perform classification and regression by maximizing the geometry margin. The SVM mapping can divide the data into higher dimensional spaces by creating a maximum separating hyperplane of the input vector. Creates two parallel planes on either side of the hyperplane that separates the data. The separating hyperplane works by maximizing the distance between two parallel hyperplanes. The larger the margin or distance between these parallel hyperplanes, the better the classification performance.

Bayes' theorem is a statistical method and dates back to ancient times. Naive Bayes (NB) is an algorithm based on Bayes' theorem and the independent hypothesis of characteristic conditions. It is based on the input/output joint probability distribution based on the independent hypothesis of characteristic conditions. According to this model, the output y with the maximum probability is calculated by Bayes' theorem for the input. This algorithm has simple implementation and high prediction efficiency [33].

A multi-layer perceptron (MLP) is a feed-forward artificial neural network consisting of one or more layers. An MLP consists of at least three layers: input, hidden, and output layers, respectively. In MLP, it is built without specifying the number of hidden layers and there is no limit to the number of neurons in the input layer. MLP is a supervised learning technique [34].

Gradient assisted machine (GBM) is also known as gradient assisted regression tree (GBRT) or gradient tree reinforcement. It is an algorithm in the category of (CART), which is a classifier with simultaneous classification and regression. GBM is known as a member of homogeneous ensembles in which several weak classifiers of the same type are used to construct a prediction model. The trees that make up the algorithm are grown sequentially, and subsequent trees are based on the results of previous trees. The forecast generated for a data forecast is the sum of the forecasts from many trees [35].

The AdaBoost classifier (ABC) was developed to identify the weak classifier that can best separate the weak learning, positive and negative samples. For each feature, the optimal threshold value is determined such that poor learning, the minimum number of samples are misclassified [36].

2.5. Cross Validation

Cross-validation is a statistical resampling method used to evaluate the performance of a machine learning model on data it does not see, as objectively and accurately as possible. The second area of use is to optimize the model for hyperparameters. In the train-test split approach, the dataset to be used in the model is divided into train and test. The model is built with the Train set and the model's performance is evaluated over the test set. Since different accuracy values are obtained as a result of different train-test splits with this method, we cannot say that we can objectively evaluate the performance of the model. Cross-validation is used to achieve this objectivity. The working method of this method is as follows. Cross validation is shown in Figure 2. In this study, the K value determined for cross-validation was chosen as 10.

1. The dataset is shuffled randomly.

2. The dataset is divided into k groups.

3. The following steps are applied for each group.

- The selected group is used as the validation set.
- All other groups (k-1 groups) are used as train sets.
- The model is built using the Train set and evaluated with the validation set.
- The evaluation score of the model is stored in a list.

4. The statistical summary of the evaluation scores is checked.

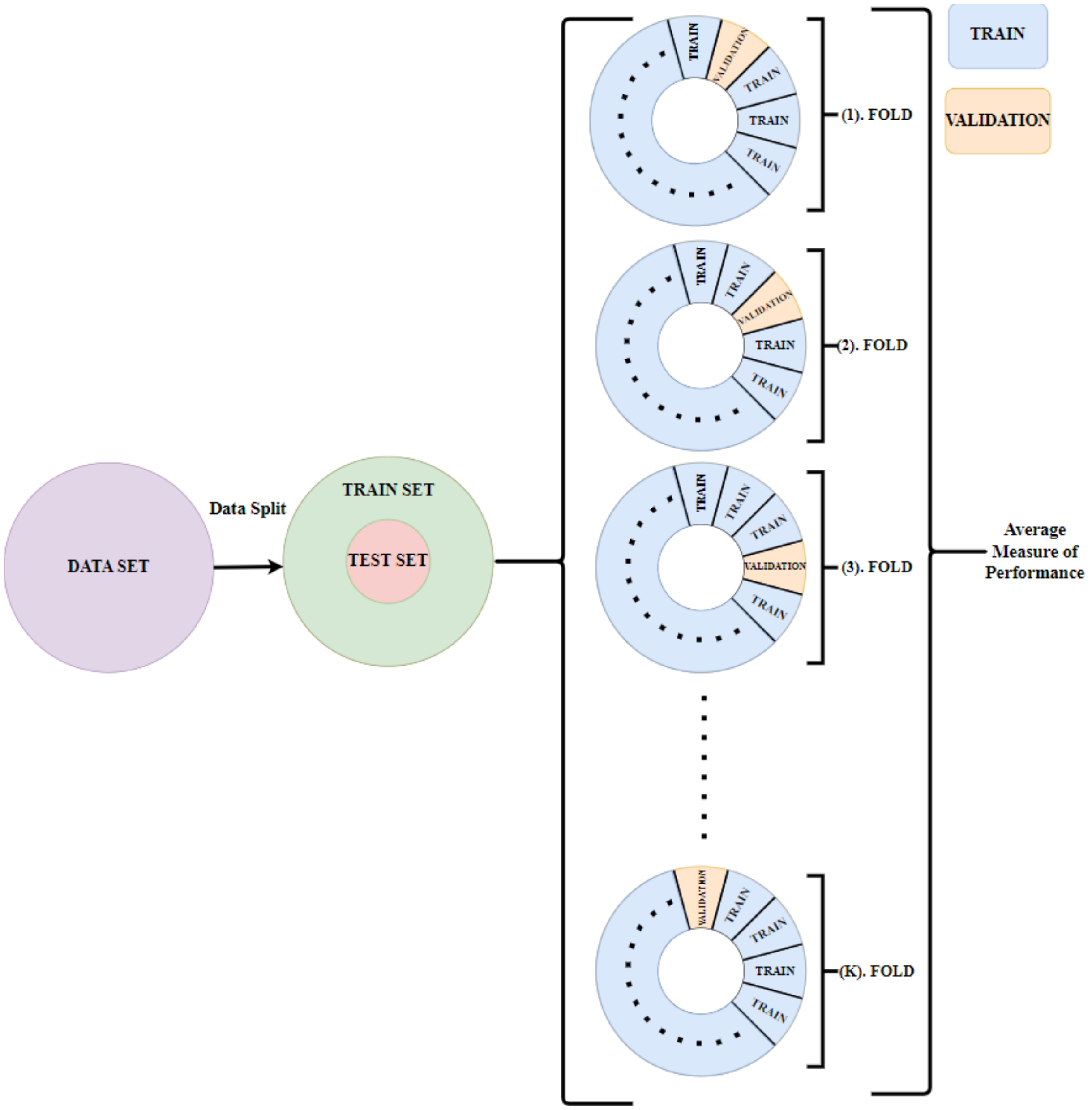


Figure 2. *K-fold cross-validation*

2.6. Hybrit Learning

In the hybrid learning method we used in our study, first feature extraction using CNN architecture and then classification with both CNN and machine learning algorithms. The flow chart is given in Figure 3.

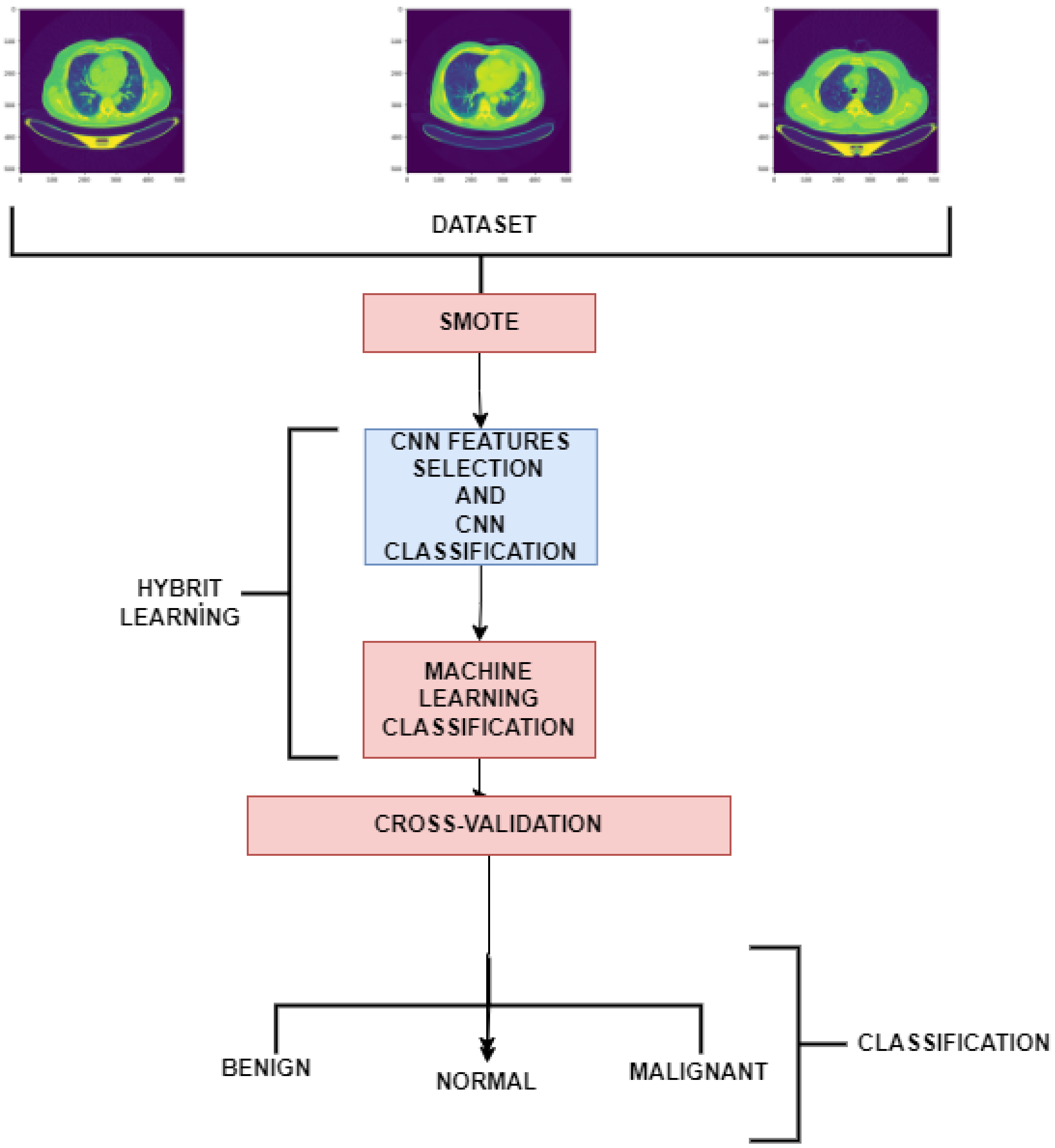


Figure 3. *Main operation and hybrid learning flowchart.*

In our study, we first applied the technique known as SMOTE to stabilize our unbalanced dataset. Then we resized the images and made them 64 x 64 x 1. Then, we made classification besides feature extraction using our CNN architecture and compared the features we extracted with CNN by subjecting them to classical machine learning algorithms.

3. EXPERIMENTAL RESULTS

In this section, we present the experimental results we obtained in our study. These results, artificial intelligence algorithms, the proposed method, libraries such as Tensorflow, Numpy, scikit learn and Pandas were used in Anaconda-based Pycharm ide. Nvidia GTX 1060 Max-Q Design was implemented on a system with 6GB GPU, 16GB DDR4 RAM and Intel Core i7-7700HQ processor.

The comparison of our results with each other and with some recent studies in the literature is given in Table 3.

Table 3. *Comparison of the methods of the studies*

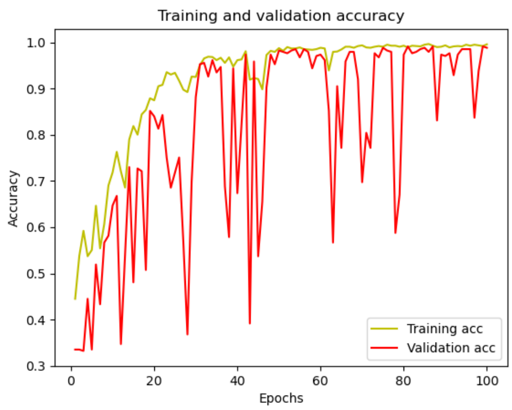
Reference	*Method of study*	*Accuracy (%)*	*Preision (%)*	*Recall (%)*	*F1-score (%)*

[11]	*AlexNet, VGG, DCNN, DensNet*	*97.48*	*97.53*	*97.53*	*97.53*
[37]	*VGG16,19 Xception*	*0.9805*	*0.9804*	*0.9766*	*0.9785*
[38]	*LeNet, AlexNet, VGG16, ResNet 50, Inception-V1*	*95.28%*	*-*	*96.77%*	*95.62%*
[39]	*MobileNet, VGG16, VGG19, DenseNet, ResNet*	*56*	*43*	*42*	*42*
Proposed method	*CNN + ML*	*99.70*	*99.71*	*99.71*	*99.71*

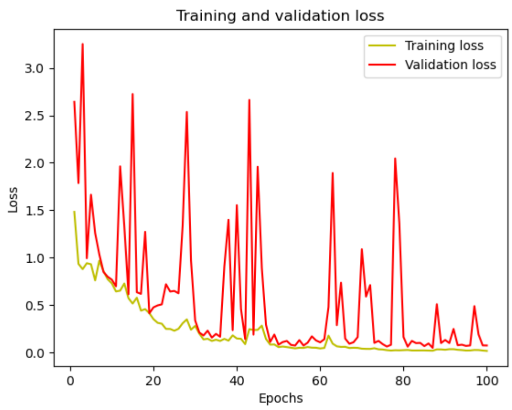
Table 4. *Comparison of the methods we tried in our study*

Method	***Accuracy (%)***	***Preision (%)***	***Recall (%)***	***F1-score (%)***
CNN + DT	*98.81*	*98.81*	*98.81*	*98.81*
CNN + RF	*99.40*	*99.40*	*99.40*	*99.40*
CNN + KNN	*94.36*	*94.36*	*94.36*	*94.36*
CNN + SVC	*95.84*	*95.84*	*95.84*	*95.84*
CNN + NB	*99.70*	*99.71*	*99.71*	*99.71*
CNN + MLP	*99.40*	*99.40*	*99.40*	*99.40*
CNN + GBC	*99.70*	*99.71*	*99.71*	*99.71*
CNN + ABC	*99.70*	*99.71*	*99.71*	*99.71*

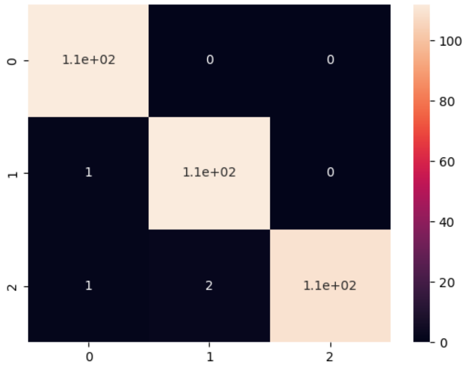
When Table 4 is examined, it is seen that the best results are CNN + GBC, CNN + ABC and CNN + NB.



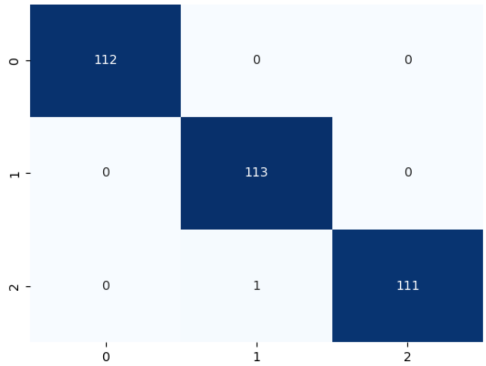
(a)



(b)



(c)



(d)

Figure 4. *Accuracy (a), loss (b) graphs of CNN classifier in our work, confusion matrix (c) and confusion matrix of best hybrid classifier (d)*

Option (a) of Figure 4 represents the accuracy of the CNN architecture, option (b) represents the loss of the CNN architecture, and option (c) and (d) represent the complexity matrix when examined. (0) represents benign, (1) malignant, and (2) normal class.

4.CONCLUSIONS

In this study, various hybrid learning architectures that we propose to detect the stages of lung cancer in humans were applied and compared with each other and with current studies in the literature. The results of our study are the best in the literature and are quite promising. The parameters against which we compare our results are accuracy, precision, recall, f1-score and confusion-matrix. When the results are examined, it is seen that the algorithms learn and make predictions without overfitting thanks to the cross-validation technique we apply, as proven by confusion-matrixes. Our best result comes from the CNN+GBC hybrid architecture. This architecture's accuracy, precision, recall, and f1-score are on average 99.71%. The CNN+GBC hybrid architecture predicted almost all classes correctly. These results will provide great convenience to healthcare professionals in terms of time and cost.

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