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Melanoma Skin Cancer Classification Using EfficientNetB7 Feature Extractor and Ensemble Learning

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ABSTRACT

Cancer remains one of the leading causes of mortality worldwide, with melanoma skin cancer recognized as one of the most aggressive and dangerous types. It primarily affects the outer layer of the skin, where cells are highly susceptible to damage. Early and accurate diagnosis is critical for effective treatment; however, current diagnostic methods are predominantly manual and may lead to delays or misdiagnosis. Although several studies have utilized deep learning for melanoma detection, the accuracy of these models can still be improved. This study aims to develop an efficient and reliable method for classifying melanoma skin cancer using a combination of deep learning and machine learning techniques. We propose the use of EfficientNetB7 as a feature extractor, followed by ensemble learning classifiers Categorical Boosting and Extreme Gradient Boosting (XGBoost) to analyze and classify the extracted features. The proposed approach achieved an accuracy of 91.2% in distinguishing between benign and malignant skin lesions, outperforming several existing methods. These results demonstrate the potential of integrating deep learning-based feature extraction with ensemble learning models to enhance diagnostic performance in melanoma classification. This hybrid model not only improves accuracy but also offers a scalable and automated solution for skin cancer diagnosis, supporting early detection and better patient outcomes.

1. INTRODUCTION

Cancer is a disease where cells in the body grow uncontrollably. Another indication of cancer such as rapid spreading to normal cell in the body, ability to resist treatment, and can happen in many parts of the body is the reason cancer become deathly [1]. Early detection of cancer can be difficult as it may not show the symptoms of the cancer in the early stage [2]. Among the various types of cancer, skin cancer is one of the most common and rapidly increasing forms worldwide [3].

Skin cancer is one of the dangerous types of cancer that attacks the human skin cell layer, because human skin is in direct contact with air pollution and sun heat [4] . This is what helps the development of skin cancer cells [5] . A severe form of skin cancer called melanoma can develop from pre-existing moles that seem black or similar in color to the surrounding skin. Moles that enlarge, change color, and become itchy are just a few of the obvious signs of melanoma skin cancer [6]. Changes in a mole's size or texture, such as growth or ulceration, can be a sign of melanoma [7]. Melanoma, although less common, is more aggressive and can be life-threatening if not diagnosed and treated promptly. In Indonesia, melanoma, a form of skin cancer, ranks 23rd, with 1,609 new cases and 699 deaths [4], [7]. Despite the high risk of melanoma, survival rates are still quite high when the disease is identified and treated early. Early melanoma detection is not just a challenging research topic but also highly significant [8].

Detection of skin cancer early on involve of visual inspection on the skin using ABCDE Rule, which stand for Asymmetry, Border irregularity, Color Variation, Diameter, and Evolving in size [7]. This method had some risk of undetected skin cancer because of the nature of visual inspection by human caused by a lot of factors such as lightning, experience and individual of the examiner [9]. Considering this, it is crucial to accurately identify and classify the various forms of skin cancer using computer-assisted skin cancer detection using various machine learning and deep learning.

Machine learning algorithm can be used to detect early stage of melanoma. By training machine learning algorithm with image of skin cancer, these algorithms can help doctor or specialist to identify early stage of skin cancer quicker [3]. Other than machine learning, researcher also using Deep neural network to classify melanoma skin cancer. Deep neural networks, a subset of artificial intelligence, consist of multiple layers of neurons that simulate the structure of the human brain. These layers can learn complex features from data, making them particularly useful for image recognition tasks with minimal image preprocessing [10]. DNNs could process large amounts of data and learn to distinguish between malignant (cancerous) and benign (non-cancerous) skin lesions with high accuracy. CNN are the most used one to classify skin cancer with a lot of researchers try to improve the architecture or by modifying the architecture of the CNN such as research from [11] where the study created 2 parts of CNN to identified global and part feature from the image called GP-CNN. Other than using CNN or modified version of it, researcher also utilizing transfer learning to improve the model classification accuracy for skin cancer.

Transfer Learning is a method to use predesign model with knowledge from the model itself without the need to retrain the model [12]. Without the need to retrain the model with new data, transfer learning increased the efficiency of the model training and decrease the time and resource needed for model training [13]. Keerthana et al. [14] use Hybrid DenseNet and ResNet-201 to extract the feature from the image, with Support Vector Machine to classify benign or malignant skin cancer. Other relevant research but different scope involving use of EfficientNetB0 and Xception model as feature extractor and Support Vector Machine using Radial Basis Function as final classifier to classify osteosarcoma with high accuracy [15]. According to the research mentioned, it can be concluded that deep learning can be a solution to extract deep feature and combined with machine learning classifier in skin cancer detection.

Other than using Deep Learning as Feature Extractor, machine learning usage can be improved using Ensemble Learning. Ensemble Learning is a method where more than one machine learning model is combined into one meta learning model to achieve best outcome [16]. This approach is effective on classification task due to decrease bias and variance while also improving general accuracy of the machine learning model [16]. One of ensemble learning method are Voting, where each of the model used might learning different feature or complementing each other, which in turn, when combined, improving final prediction accuracy of the model [17]. There are different kind of voting algorithm, one of them are Majority Voting, where each of the classifier cast a prediction then prediction with the most vote is selected [17]. Example of the use case of majority voting can be seen by Inthiyaz et al. [18] using combination of CNN, KNN, SVM, and combination of all three-method using majority voting, where the majority voting improves the accuracy of skin cancer detection, further highlighting the importance of using Ensemble Learning method.

This research will be carried out to improve accuracy of skin cancer classification model by using EfficientNet as a Feature Extractor and combined XGBoost and CatBoost into one ensemble model using majority voting. The newer dataset from Kaggle was employed with more data than past research with aims to contribute in better skin cancer classification model using combination of deep learning as feature extractor and machine learning to classify skin cancer.

2. RELATED WORK

Research has been done on the detection of skin cancer types with several machine learning and deep learning algorithms. Keerthana et al. [14] proposed a method with Hybrid DenseNet-201 and MobileNet with Support Vector Machine to classify between melanoma or benign skin cancer. The pre-trained network was used to extract the feature from the image. After that, SVM was used to classify the feature. ISBI-2016 dataset was used consist of 900 images with 733 images for training and 167 images for testing was used to train and test the model. The hybrid-CNN model with SVM Classifier reach accuracy of 88.02%.

Another research from Inthiyaz et al. [18] utilize Convolutional Neural Network, KNN, SVM, and combination of them using majority voting. Dataset ISIC Archive was used consist of 640 benign and malignant images. The model reached 88.4% accuracy by combining CNN, KNN, and SVM using majority voting. Research from [11] using GP-CNN and P-CNN to extract the global feature of the image using Global Convolutional Neural Network and P-CNN to extract the local and subtle feature of the image using Part Convolutional Neural Network. Both of network is used to tackle the issue with inter-class similarity and intra-class variation of the image while using limited dataset. ISIC-2016 and ISIC-2017 dataset was used to train and test the model. The model reached 85.1% accuracy on malignant and benign classification.

Kandhro et al [19] use Enhanched-VGG19 (E-VGG19) to classify benign or malignant skin image. Dataset ISIC-2020 was used to train and test the network. The model reached 88% accuracy to classify benign or malignant skin cancer. However, the past research [11], [14], [18] have some problem particularly with very small dataset and imbalance data for benign/melanoma classification. Other research [19] have much better dataset but still lack of accuracy. This study proposed a new method utilizing Transfer Learning as Feature Extraction and comparing few machine learning classifier methods to be classify extracted melanoma skin cancer dataset from the feature extractor. EfficientNet will be used Feature Extractor and XGBoost, CatBooost, and combination of both using Majority Voting to classify benign or melanoma skin cancer. This method hopefully improves accuracy of skin cancer classification. This research also uses a new dataset with more image for benign or malignant skin. cancer classification to further improve the classification ability of the model.

3. METHODOLOGY

The proposed method uses EfficientNetB7 Feature Extractor and Ensemble Learning to classify benign or melanoma skin cancer. First, data collection was carried out. After that, image pre preprocessing is needed by normalizing the data to improve accuracy and training time of the model. Then, EfficientNetB7 is used to extract the feature from the dataset. Feature that extracted is trained to both XGBoost and CatBoost to produce the accuracy of the skin cancer classification. Each model is combined using Majority Voting method to improve accuracy. Flow of the proposed skin cancer classification model can be seen from Figure 1.

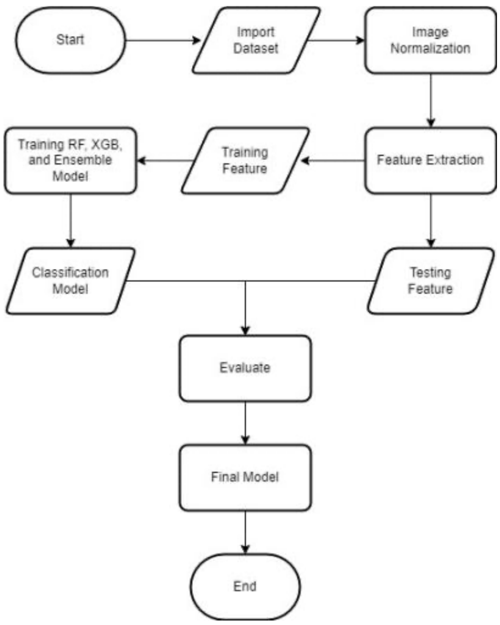

FIGURE 1. RESEARCH METHODOLOGY

3.1 Data Collection

The skin cancer dataset used in this research is "Melanoma Skin Dataset of 10000 Image" from Kaggle.com consist of 9605 images for training and 1000 image for testing [20]. The author of the dataset collected the image data from different image in ISIC dataset. Training images consist of 5000 benign image and 4605 malignant image of skin cancer.

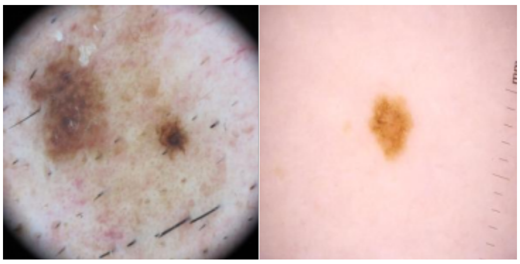

FIGURE 2. EXAMPLE OF MELANOMA (LEFT) AND BENIGN (RIGHT)

Test images consist of 500 benign image and 500 malignant image of skin cancer Figure 2 are the image example from the dataset.

3.2 Data Pre-processing

Data pre-processing is carried out after data collection. Skin cancer dataset will get preprocessing treatment such as image normalization. Math formula for image normalization used in this study math are shown below on Equation 1.

$$normalized\ pixel = \frac{original\ pixel}{255} \tag{1}$$

This equation is performed on every pixel of each image. Image normalization is used to convert the pixel range from 0 to 255 into 0 to 1 format. This will reduce computational cost which in turn reduce the resource needed to train the network and reduce the training time of the feature extractor.

The implementation of this formula is performed by keras library called Image Data Generator by adding argument rescale. Flow From Directory also be used to generate batch image with parameter describe in Table 1.

TABLE 1. FLOW FROM DIRECTORY PARAMETER

Directory	Train, Test
batch_size	32
class_mode	None
target_size	300, 300
shuffle	False

3.3 Feature Extractor Model

EfficientNet was used for extracting feature from the image on the dataset. This model was chosen because high accuracy while also using less computation resource using compound scaling method to balance the network depth, width, and resolution [21]. This architecture also used grid search method to form relationship between several network scaling when training with limited resource [22]. Construction of EfficientNet consist of Mobile Inverted Bottleneck Convolution (MBConv) Block with Squezze-and-Excitation optimization [23]. Squezze-and-Excitation is an adaptive unit that recalibrate channel-wise feature responses by explicitly modeling the interdependencies between channels, adaptively recalibrate the channel-wise feature responses [24]. Figure 3 is the construction of EfficientNetB7 as feature extractor.

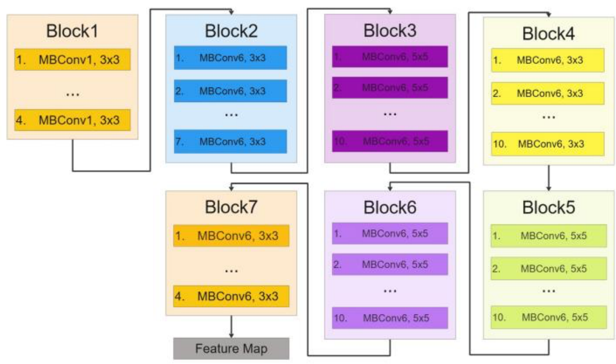

FIGURE 3. EFFICIENTNETB7 CONSTRUCTION

In this study, EfficientNetB7 is used for feature extractor model to extract feature from image. The base model is loaded with weight from imagined and removed top layer to be configure with custom top layer. The layer of each of the base model are frozen to prevent the weight being updated in the training process to preserve the learned feature from original weight of imagined trained in EfficientNetB7. Top layer was changed to custom top layer consist of Flatten layer to convert the feature map to single continuous vector and output layer constructed from Dense Layer with 256 Unit and ReLU activation. Then, model is compiled with RMSProp optimizer with learning rate=0,001 and binary cross entropy loss function.

3.4 XGBoost Model

XGBoost is an algorithm developed for speed and performance by iteratively build multiple models where the new one continuously corrected the error of the predecessor model, and the final prediction is based on weighted summation of all models created [25]. The core of the algorithm is based on decision tree but with added feature like regularization and tree pruning to reduce overfitting, meaning the algorithm will better fit in both training and testing data [26]. XGBoost's advantages in memory usage and ability to handle imbalanced data make it easier for practitioners to choose the algorithm that best suits their needs. Therefore, the selection of the right algorithm is crucial to achieve optimal results in a data analysis project. In addition, it is important to consider additional elements such as model interpretability and ease of implementation, as these factors can influence the final decision on the chosen algorithm. By considering all these elements, researchers can hopefully make more informational and strategic decisions when developing models [26].

In this study, XGBoost is utilized for classifying feature extracted from skin cancer dataset. Prediction of XGBoost model will be evaluated using metric describe later after this section. XGBoost model also will be used as part of Ensemble Learning in the next experiment. The hyperparameter that XGBoost used in this study will be explained on Table 2.

TABLE 2. XGBOOST HYPERPARAMETER

Hyperparameter for XGBoost	
n_estimator	100
random_state	None

3.5 CatBoost Model

This algorithm work by combining several weak learners into single strong ensemble classifier [26]. Another feature of this algorithm including categorical feature handling without needing one-hot encoding and capable of handling imbalance data by employing objective function that consider the class distribution of the data [27]. The base model used by CatBoost is a fully symmetric tree, and the same splitting criteria are applied at every layer. CatBoost makes use of categorical characteristics, which greatly increase the dimensionality of the features and enhance prediction stability and speed [27]. CatBoost in this study is used for classifying skin cancer from the feature extracted by feature extraction model. Later in this study, this model will also be used as part of Ensemble Learning model with XGBoost to further improve the accuracy of the skin cancer classifier. Hyperparameter used in this study are shown in Table 3.

TABLE 3. CATBOOST HYPERPARAMETER

Hyperparameter for CatBoost	
iterations	1000
learning_rate	0,1
depth	5
silent	True

3.6 Ensemble Model using Majority Voting

Ensemble Learning is a method that combine multiple machine learning model into single model to improve overall performance of the model [28]. This can be done by homogeneous model with same type of model but with different hyperparameter or size, or heterogeneous model with different model [29]. In general, the training groups are divided into parallel groups and sequential groups. The former trains the algorithm models independently before being combined to improve the final accuracy [30]. The bagging model, which utilizes parallel base training generation to drive model group variation, is the most popular model of the parallel training group. Sequential groups, on the other hand, are less suitable for inquiry training.

One form of Ensemble Learning used in this study is Majority Voting. Majority Voting or Hard Voting work by integrate every class prediction from various classifier with each one provide their class prediction and the class with most vote will be chosen as prediction [31]. XGBoost and CatBoost model will be retrained together using Voting Classifier from Sklenar library. The hyperparameter used in Voting Classifier as shown in Table 4.

TABLE 4. VOTING CLASSIFIER HYPERPARAMETER

Hyperparameter for Voting Classifier	
Estimator	xgb, cbc
voting	hard

Estimator is the classification model that has been stated before this section. Voting need to be set 'hard' since in this study will use Majority Voting Classifier. The process will start from training together both XGBoost and CatBoost classifier. After that, the new combined model will predict test dataset.

3.7 Model Evaluation

Model was evaluated with accuracy, precision, recall, and F1-score. Accuracy metrics calculate how accurate the model classified benign or malignant class from the dataset. Precision metrics calculate how many predicted positive data positives. Recall metric calculate how many positive data are correctly predicted positive. An F1 Score metric calculate mean between Precision and Recall. All the metric is calculated with Equation (2), (3), (4), (5).

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$precision = \frac{TP}{TP+FP} \tag{3}$$

$$recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1\,Score = 2 \times \frac{recall \times precision}{recall + precision} \tag{5}$$

With is True Positive, the amount of positive data predicted positive, is True Negative, the amount of negative data predicted negative, is False Positive, the amount of positive data predicted negative, and is False Negative, the amount of negative data predicted positive.

4. RESULT AND DISCUSSION

This section contains the implementation of the planned stages in the Methodology section, including testing and analysis of test results or analysis of research results in general. In this section, you can add tables or pictures.

4.1 XGBoost Classifier

XGBoost Classifier achieved 90,7% accuracy when classifying the skin cancer feature extracted with EfficientNetB7. Table 5 explain the XGBoost model performance metric such as: the accuracy, precision, recall, and F1-score of XGBoost Classifier when classify skin cancer.

TABLE 5. RESULT FROM XGBOOST CLASSIFIER

XGBoost Result	
Accuracy	90,7%
Precision	91%
Recall	91%
F1-Score	91%

4.2 CatBoost Classifier

CatBoost Classifier achieved 90,2% accuracy when classifying the skin cancer feature extracted with EfficientNetB7. Table 6 explain the CatBoost model performance metric such as: the accuracy, precision, recall, and F1-score of CatBoost Classifier when classify skin cancer.

TABLE 6. RESULT FROM CATBOOST CLASSIFIER

CatBoost Result	
Accuracy	90,2%
Precision	90%
Recall	90%
F1-Score	90%

4.3 Ensemble Classifier

Ensemble Classifier achieved 91,2% accuracy when classifying the skin cancer feature extracted with EfficientNetB7. Table 7 explain the Ensemble model performance metric such as: the accuracy, precision, recall, and F1-score of Ensemble Classifier when classify skin cancer.

TABLE 7. RESULT FROM ENSEMBLE CLASSIFIER

Ensemble Learning	
Accuracy	91,2%
Precision	91%
Recall	91%
F1-Score	91%

4.4 Discussion

The experiments conducted in this study produced three different classifiers for melanoma skin cancer classification. Table 8 presents a detailed comparison of these classifiers, highlighting their performance, accuracy, and effectiveness based on the extracted features. This comparison provides insights into the strengths of each model for reliable melanoma diagnosis.

TABLE 8. COMPARATION OF EACH CLASSIFIER.

Method	Metric			
	Precision	Recall	F1-Score	Accuracy
XGBoost	90%	91%	91%	90,7%
CatBoost	90%	90%	90%	90,2%
Ensemble	**91%**	**91%**	**91%**	**91,2%**

By combining 2 classifiers into Ensemble Learning using Majority Voting, the accuracy of the classifier improves by 1% between Ensemble and CatBoost Classifier and 0.5% between Ensemble and XGBoost. Other than metric comparation, this study also produced confusion metric of each classifier. Figure 4 are the confusion matrix of each classifier.

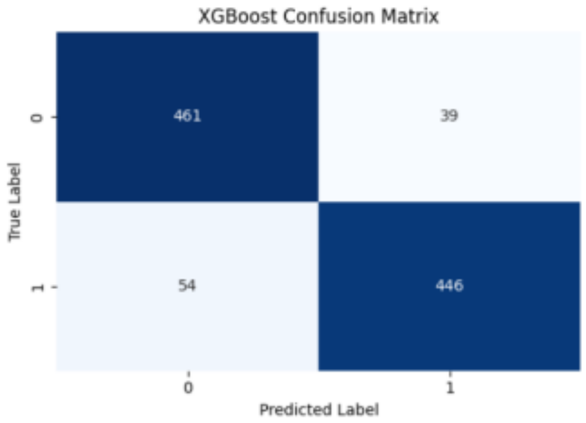

FIGURE 4. CONFUSION MATRIX OF XGBOOST CLASSIFIER

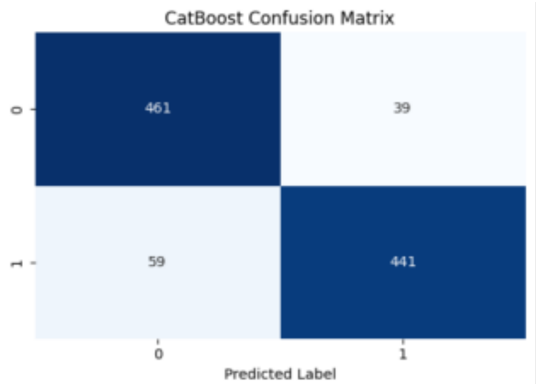

FIGURE 5. CONFUSION MATRIX OF CATBOOST CLASSIFIER

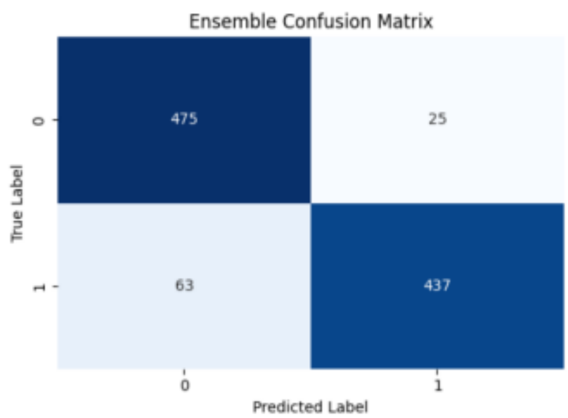

FIGURE 6. CONFUSION MATRIX OF ENSEMBLE CLASSIFIER

XGBoost Classifier successfully recognize 461 benign skin and 446 malignant skins from 500 of each image. There are 39 benign images misclassified as malignant and 54 malignant image misclassified as benign image. Then, CatBoost Classifier successfully recognize 461 benign skin and 441 malignant skins from 500 of each image. There are 39 benign images misclassified as malignant and 59 malignant image misclassified as benign image. It can be concluded the CatBoost model perform little worse than XGBoost model with 5 more malignant image misclassified as benign image. After that, Ensemble Learning Classifier using combination of XGBoost and CatBoost Classifier using Majority Voting successfully recognize 475 benign skin and 437 malignant skins from 500 of each image. There are 25 benign images misclassified as malignant and 63 malignant image misclassified as benign image. It can be concluded that Ensemble Model perform better with 14 less benign image misclassified as malignant, but with sacrifice extra 5 malignant images misclassified as benign. Therefore, Ensemble Learning improve the accuracy of the model.

Based on the result described earlier, the proposed model to classify melanoma skin cancer is compared in Table 9. The proposed methods are XGBoost, CatBoost, and Ensemble Learning.

TABLE 9. COMPARATION FROM PREVIOUS RESEARCH

Author	Method	Accuracy
Keerthana et al. [14]	Hybrid DenseNet and ResNet201 + SVM	88.02%
Gouda et al. [32]	Inception-v3	85.7%
A. Javaid, M. Sadiq and F. Akram [33]	Image Processing and SVM	88%
Proposed	**EfficientNetB7 + Ensemble Learning**	**91.2%**

From the comparison in Table 4 above can be concluded that the accuracy obtained from the proposed method using EfficientNet as a Feature Extractor and Ensemble Learning as classifier is better than previous method with accuracy of 91.2%, outperforming other Deep Learning method such as Inception-v3 [32] and combination of Deep Learning and Machine Learning using Hybrid DenseNet and ResNet201 with SVM as feature classifier [14]. Therefore, it can be said the proposed model is more optimal than previous research model.

5. CONCLUSIONS

Cancer is a disease in which cells in the body grow uncontrollably. Other signs of cancer include rapid spread to normal cells in the body, the ability to resist treatment, and can occur in many parts of the body. Skin cancer is one of the most dangerous types of cancer that attacks the human skin cell layer because human skin is in direct contact with air pollution and the heat of the sun. A serious form of skin cancer called melanoma can develop from pre-existing moles that appear black or similar in color to the surrounding skin. Moles that get bigger, change color and become itchy are some of the obvious signs of melanoma skin cancer. Recently, there have been some research to explore how to automate the process of skin cancer detection. Various techniques have been used to detect skin cancer using machine learning or deep convolutional network. However, the previous research has some problems especially with very small dataset and unbalanced data for benign/malignant classification. Other research has much better data but still lacks accuracy. New method and skin cancer dataset are needed to further improve accuracy of the skin cancer classification. This study proposed EfficientNet Feature Extractor and Ensemble Classification model with a combination XGBoost and CatBoost can be used to classify melanoma skin cancer with good accuracy of 91.2%. Ensemble Learning is proved can increase accuracy of skin cancer classification. The model can distinguish either benign or malignant skin accurately. Future research can be done to decrease the false detection rate to further improve accuracy of the model.

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