2022 IEEE 28th International Conference on Parallel and Distributed Systems (ICPADS) | 978-1-6654-7315-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICPADS56603.2022.00020

Melanlysis: A mobile deep learning approach for early detection of skin cancer

Samen Anjum Arani†, Yu Zhang*†✉, Md Tanvir Rahman† and Hui Yang*‡
*Key laboratory of Flexible Electronics of Zhejiang Provience,
Ningbo Institute of Northwestern Polytechnical University, Ningbo, China
†School of Computer Science, Northwestern Polytechnical University, Xi'an, China
‡School of Life Science, Northwestern Polytechnical University, Xi'an, China
samenanjumarani@outlook.com, zhangyu@nwpu.edu.cn, mdtanvirrahman02@outlook.com

***Abstract*—Early detection of melanocytes can save lives from melanoma. Most individuals can't be professionally diagnosed since it's time-consuming, costly, and inconvenient. Smartphone-based early skin cancer diagnosis has emerged as a new approach. The existing computer-aided skin cancer diagnosis methods and mobile deep learning technology have been studied, and it is found that the existing smartphone-based skin cancer detection and identification methods rely on the support of background cloud services. Accuracy, reaction time, and patient data confidentiality are issues. A novel early detection and recognition model of melanoma skin cancer based on mobile deep learning, Melanlysis, is proposed. The model uses the EfficientNetLite-0 deep learning model to have low latency and considers the imbalance of the existing open-source skin image dataset. The proposed classification model is implemented and evaluated. Experimental results show that compared with the existing EfficientNetLite-0, MobileNet V2, and ResNet-50 models, the accuracy of correctly identifying malignant or non-melanoma is over 94%. At the same time, an Android application based on this mobile deep learning model was developed to diagnose potential malignant melanoma. Users can quickly obtain the classification results of melanoma through the application.**

***Index Terms*—Melanlysis , Melanoma, Dermoscopic image, Mobile deep learning, TensorFlow Lite, Smart Health.**

I. Introduction

Melanoma and non-melanoma skin cancers are the 19^th and 5^th most often diagnosed malignancies, respectively [1]. In terms of incidence and mortality, melanoma is the most frequent and most dangerous form of skin cancer. While other forms of skin cancer are less harmful, if not detected and treated early enough, melanoma poses a greater threat. Australia, Canada, and the United States have seen a steady rise in the number of people diagnosed with skin cancer in recent decades [2-4]. Melanoma is expected to claim the lives of 6,850 Americans in 2020 [5] as a result of a projected diagnosis of 100,350 new cases. [6] Estimates from WHO's Global Cancer Observatory show that the number of instances of melanoma skin cancer detected globally would rise by 18% to 340,271 by 2025; the number of deaths will rise by 20%. There will be an increase of 62% in skin cancer diagnoses and 74% in the number of deaths due to melanoma in the United States by 2040. Europe has just 9% of the world's population, yet it accounts for 25% of the world's cancer cases. More than 3 million new cancer diagnoses and 1.93 million deaths from cancer were expected in Europe in 2018 [7]. It is predicted that the number of new cases of melanoma will grow by 5.8% in 2021 [8].[9] An estimated 99,780 cases of melanoma will be detected in the United States in 2022, with around 57,180 cases identified in males and 42,600 cases diagnosed in women, according to the American Cancer Society.

The need for remote automated diagnostic technologies is expanding as the burden of skin cancer on global healthcare systems grows. Melanoma, like other malignant cells, has the potential to spread swiftly to other regions of the body, inflicting significant harm. Despite this, the likelihood that malignant cells may spread to other organs is minimal in the early stages of melanoma. Because this malignancy is skin-based, early detection is feasible. Recent improvements in the area allow for earlier detection of melanoma. First and foremost, dermoscopy has improved clinical diagnostic capabilities, enabling the early diagnosis of melanoma in the clinic. The extensive usage of dermoscopy technologies has resulted in enormous data collections. Patients in poor countries lack access to the most advanced medical equipment and diagnostic knowledge.

When the studies are considered, the usage of artificial intelligence and deep learning methods in the classification of skin cancer demonstrates the efficacy of these technologies and approaches. Previously, the vast majority of solutions relied on a central server or cloud server to store data and do all computations, respectively. It is difficult to utilize deep learning models on mobile devices, due to the lack of resources such as storage and power. Thus, using the notion of Mobile Cloud Computing (MCC) we may deploy deep learning models since the MCC has computing resources. Since mobile devices and cloud platforms need to work together to achieve this model's objectives, however, they come with a number of disadvantages. Security and efficiency have become more difficult tasks in healthcare apps, which motivated us to deploy a new library called TensorFlow lite, which enables users to execute machine-learning models on mobile devices with minimal latency.

The most significant contribution made by this thesis is,

1. Our research focused on identifying deep learning algo-

978-1-6654-7315-6/23/$31.00 ©2023 IEEE
DOI 10.1109/ICPADS56603.2022.00020

rithms that are appropriate for mobile deep learning in the context of issues such as data privacy as well as latency, and reaction time. We present the "Melanlysis" on-device inference app, which pre-trains and stores a classification model on a mobile device.

2. We propose to use the WGAN algorithm to generate synthetic skin cancer medical pictures in order to increase the classification model's accuracy. A growing number of samples and high-quality skin lesion imaging help dermatologists draw increasingly accurate diagnostic judgments utilizing this technology.

3. For skin cancer detection tasks, we leveraged EfficientNetLite-0 for our deep learning model. It was found that EfficientNetLite-0 would be the optimum because of low latency, which is very important for mobile deep learning. In order to compare the capabilities of our proposed model, EfficientNetLite-0, MobileNet V2 and ResNet-50 were also tested in conjunction with it. In addition, we concentrated on a two-class issue rather than identifying distinct forms of skin malignancies as the primary emphasis. In our research, a lesion was either categorized as melanoma or non-melanoma.

4. We use TensorFlow-lite to deploy the more effective classification model into the pre-existing mobile app "Melanlysis" and analyze the app's performance. In addition to reducing latency, this method also saves bandwidth and increases confidentiality.

II. Literature Review

Classification of three distinct lesions is carried out by [10] using AlexNet as a transfer learning model. Only the PH2 dataset was used to train and test the suggested system, and although the accuracy rates were good, the method's credibility suffered as a result of only using one dataset. Although the findings were remarkable despite the small dataset (PH2), a different approach was used by [11], who used two pre-trained models (VGG16 and Alex Net) and experimented on the PH2 dataset. To test the performance of a model, a large number of data points must be gathered. Aside from that, deep convolution neural networks are used by [12]. The study's biggest drawback was the use of fewer photos for uncommon malignancies such as actinic keratosis, dermatofibroma, and vascular lesions than was necessary. The suggested model by [13] uses data from the PH2 study. This model must be tested on several datasets including a high number of photos for training if it is to be as accurate as possible. When the number of photos in a dataset is reduced, the results are more efficient.

Like the previous works, [14] used transfer learning, while [15] combined deep learning with feature vectors. The dual deep CNN presented by [16] may mutually learn from each other, in contrast to the dual deep CNN proposed by this for evaluating their strategy, [17] combined a deep regional convolutional neural network (RCNN) with Fuzzy C-mean (FCM) clustering. They used just the ISBI 2016 dataset. [18] employs transfer learning and [19] incorporates fully convolutional neural network, they applied their techniques using the ISBI 2016 dataset, these approaches need huge datasets to compute real results. Due to a lack of images, the results of these research are a little unclear. For effective results, [20] used transfer learning, while [21] used CNN with feature vector and [22] used region average pooling technique (RAPooling) RankOpt in their work, both of which used ISBI 2017 datasets to verify their findings. For the confirmation of their findings, [23] developed two fully convolutional neural networks, using the ISBI 2017 datasets. VGG-Net, ResNet50, InceptionV3, Xception, and DenseNet are all pre-trained models used by [24] in their analysis of ISBI 2018. [25] offer an ensemble CNN, which may improve outcomes when evaluated on the ISIC 2018 dataset [26] on the other hand, offered a constructed ensemble approach that employs the ISBI 2018 dataset and obtains the best possible accuracy.

In addition, [27] used CNN and a novel regularize to classify skin lesions, whereas [28] suggested neural networks with feature selection and tested their findings using the ISIC archive. This database has more than 23,000 photos of various skin tumors, which improves the method's performance. Aside from this previous work, [29] created Predict-Evaluate-Correct K-fold (PECK), Synthesis and Convergence of Intermediate Decaying Omni gradients (SCIDOG), which trains ensembles using limited data while SCIDOG easily identifies lesion even if there is noise in the picture. Using the Mednode dataset, which includes 170 pictures, these algorithms were used to identify melanoma from benign photos. To get the most out of both types of features, [30] suggested an approach that employs mutual information measures to combine deep learning features with handmade features. Linear regression, support vector machines, and relevant vector machines are used in the suggested technique for classification. The suggested strategy was tested on the ISBI challenge 2018 and found to be effective. According to [31], a multiclass multilevel algorithm may be used to classify skin lesions based on their characteristics. Traditional machine learning and deep learning techniques were used in the development of the model. To reduce the network output error for skin lesion categorization, [32] developed an optimization approach. DSNet, a semantic segmentation network for segmenting skin lesions, was suggested by [33].

A lightweight network was created using depth-wise separable convolution, which reduced the number of parameters. Segmenting skin lesions using CNN was suggested. In order to build the CNN, we started with a tiny dataset that had been augmented. Image enhancement was used by [34] (a variant of SMOTE). They then used SquuezeNet to classify skin lesions as either benign or malignant. ISIC2018 was classified using Alexnet and transfer learning by [35]. Lesion segmentation was approached in a variety of ways. With the use of the ISIC2019 dataset, [36] developed a computer-aided design (CAD) system for skin lesions. There are a number of issues with this dataset, including classes that are unbalanced and unknown photos. The bootstrap weighted classifier was used in conjunction with a multiclass SVM. The weights of this classifier were adjusted based on the picture class.

SkinVision has a better track record of detecting skin cancer

early than other similar applications. The SkinVision app relies on detailed research to discover abnormalities. Initially, SkinVision used arule-based fractal algorithm [37] that analyzes both pigmented and non-pigmented lesions [38]. SkinVision utilizes an internet connection to upload photos to the server for analysis and reporting purposes. The eSkin [39] application also used a client-server architecture to reduce the computational load on cellphones and to allow for algorithm changes. The time and error rates associated with executing image processing on a smartphone device are two of the primary reasons for doing it on a server. Melanoma, on the other hand, is more prevalent in rural places where internet access is restricted. The smartphone device must thus be used for picture analysis in this case [40].

[41] Developed an integrated iOS mobile application for skin cancer diagnosis that made use of a convolutional neural network. In order to train the model, 10,000 dermoscopy images were used, which were divided into seven distinct categories of skin lesions. Because it is based on dermoscopy images, it is required to have a dermatoscope linked to a smartphone in order to utilize the app. This is a constraint due to the fact that such a gadget is pricey and not often accessible in rural locations. Aside from that, it does not make use of clinical data to enhance performance. Using Support Vector Machine (SVM) training on a dataset consisted of 20 photos of three different kinds of skin lesions, Phillips, [42] developed an Android application to identify melanoma . As an alternative to using an embedded solution in a smartphone device, the authors chose to run the model on a server instead. Due to the fact that the model was trained using a small number of examples, its performance is restricted.

III. Methodology

A. Proposed Architecture

As mentioned previously, a mobile deep learning strategy using TensorFlow frameworks for image classification through a smartphone is being implemented to serve the purpose of identifying melanoma skin cancer at an early stage. Our classification algorithm is trained on dermoscopic images rather than clinical photos to assist the general public prior to seeing dermatologists.

Melanlysis is a revolutionary mobile deep learning-based technique that will be used to identify skin cancer-affected lesions Fig. 1. It will be used as an application for detecting skin cancer-affected lesions.People may use this program to evaluate their diseased lesions in the shortest amount of time possible, saving them the trouble of having to see a demrologist on a regular basis. After opening the program, the patient will utilize the capture feature to take a photo of the suspected lesion. The picture will be used as an input by the mobile deep learning model that has been deployed in the application and is already trained. The picture will then be processed by this binary classification model, with the classification result being shown in two categories: melanoma and non-melanoma.

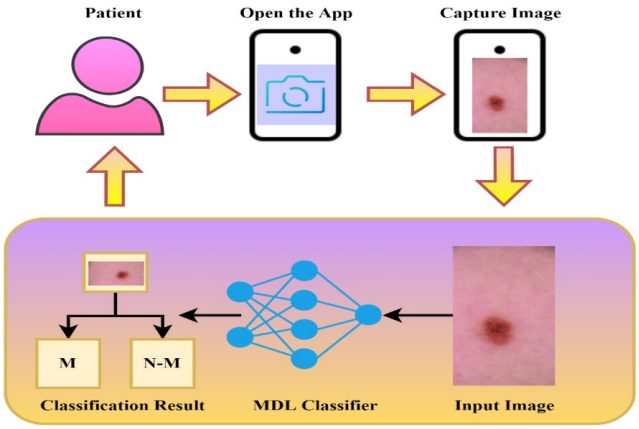

Fig. 1. Melanlysis System Architecture.

The patient will be notified of the result of the procedure. It will aid the patient in making the choice to consult with a dermatologist in the first place. Our proposed architecture implementation workflow can be separated into four major portions, which are as follows: data augmentation, model training, result evaluation, and model implementation after compression. Starting with data augmentation, which involves gathering data from internet resources, preparing the data to make it more machine-readable, and augmenting the data using WGAN. Then the classification models are built and trained on the preprocessed data. Lastly, compress the model and convert the pre-trained model into a tf.lite file, which has been implemented in the mobile application. Finally, the application was put into use.

B. Data augmentation

Our dataset is quite unbalanced, as we described previously. Inter-class imbalance applies to a binary image classification issue in which a minority class has a lower number of examples than cases belonging to the majority class. Binary classification entails assigning an input picture to one of two classes. A preprocessing step is required to balance the courses before training begins in order to resolve this problem. The number of samples available for the models was greatly increased by using supervised data augmentation procedures. Using data augmentation approaches, it is feasible to enhance the diversity of data available for training models without actually collecting extra data. The modifications obtained by WGAN include eliminating the difficulties of training difficulty, correcting the instability of GAN, and avoiding mode collapse. Furthermore, the lower the loss function of GAN, the greater the quality of the related produced data. WGAN is made up of two parts: one is the generation mode, and the other is the discrimination mode. It takes random noise from a latent space and generates unique pictures that mirror the feature distribution of the original dataset.

A WGAN takes the Wasserstein-1 Distance for its loss function, converting the discriminator into a ”critic” that

forecasts how probable a sample is from the original data set. The "Discriminator" in a GAN has the primary task of assessing false and genuine samples, identifying each sample as "fake" or "real." The batches of actual samples are provided to the discriminator from the original dataset, while the false samples originate from the Generator. The "Generator," as implied by the name, has the aim of taking in random noise from a latent space as an input and constructing "fake" data to be passed to the discriminator. The generator's purpose is to produce visuals that are so realistic that the discriminator believes they are genuine. The weights in this noble WGAN get updated considering the loss values.

$$W_x^* = W_x - a(\frac{\partial Error}{\partial W_x}) \tag{1}$$

Here, W_x^* is the new weight, W_x is the old weight, a represents the learning rate and $(\frac{\partial Error}{\partial W_x})$ is the derivative of the error with respect to the weight. Through the use of backpropagation to adjust the weights and biases of these models over time, the generator will progressively learn to make samples that replicate the physical and mathematical distribution of the original dataset.

Below the algorithm of WGAN is given:

Algorithm 1: WGAN ; The thesis experiments used default values $\alpha = 0.001, C = 0.1, m = 64, n\_critic = 5$.

Data: α, the learning rate c, the clipping rate m, the batch size n_critic, the number of iteration of the critic per generator iteration
Data: ω_0, initial critic parameters, θ_0, intital generator's parameters
while θ *has not converged do* **do**
  for $t = 0, \ldots, n_{critic}$ **do**
    Sample $\{x^i\}_{i=1}^m \tilde{} P_r$, a batch from the real data
    Sample $\{z^i\}_{i=1}^m \tilde{} p(z)$, a batch from the real data
    $g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^m f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right]$
    $\omega \leftarrow \omega + \alpha \cdot RMSProp(w, g_w)$
    $\omega \leftarrow clip(w, -c, c)$
  end
  Sample $\{z^i\}_{i=1}^m \tilde{} p(z)$, a batch of prior samples
  $g_w \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))$
  $\theta \leftarrow \theta - \alpha \cdot RMSProp(w, g_\theta)$
end

C. Classification model

Classification is the process of giving a classification to an image, such as Melanoma or Non-Melanoma. Classification is a fairly popular use of deep learning, and many classification methods are utilized to handle picture classification issues. Numerous lightweight classification methods are being developed as a result of the resurrection of mobile deep learning. We use two of the most efficient.

Due to the fact that EfficientNet-Lite 0 models are optimized for edge devices rather than the complete EffcientNet B0 models, we employed them in this application rather than the full EffcientNet B0 models.Squeeze-and-excitation networks are eliminated in EfficientNet-Lite 0 and ReLU6 activation functions are used in place of swish activation functions to support the quantization needed by edge computing devices. For our Melanlysis model, we chose the EfficientNet Lite 0 model as our base model. The EfficientNet Lite 0 technique served as the foundation for our lightweight model's design. All of EfficientNet Lite 0's layers are included in the proposed method, as well as the batch normalization layers Fig. 2 that were added to improve performance. One of the most important features we include in our model is batch normalization.

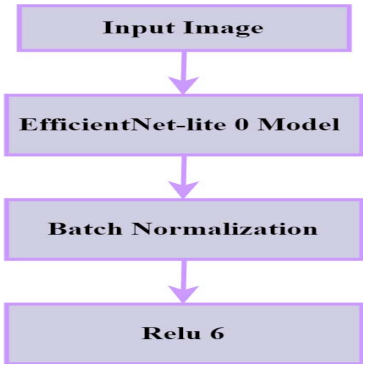

Fig. 2. Melanlysis Architecture.

As a backpropagation regularizer, it normalizes and accelerates convergence. Batch Normalization outperforms the original model by a wide margin when used with a cutting-edge image classification model, using just a fraction of the training steps. [43] Either after or before the input layer's activation function, Batch Normalization may be included. In most cases, researchers found that applying Batch Normalization after the activation layer had positive outcomes. When we came up with our suggested model, we included Batch Normalization after activating the output layer. We can speed up the training process by using Batch Normalization. Learning and accuracy are improved by the ability to adjust the mean and variance of each mini-batch independently.

TABLE I
MELANLYSIS MODEL PARAMETERS

Parameter	Value
Epoch	40
Batch Size	32
Learning Rate	1e-5
Drop Rate	0.2
Optimizer	Adam
Loss Function	Binarycross Entropy Loss
Activation Function	Relu 6

We define an initial learning rate of 1e-5 and a drop rate of 20% .The Adam optimizer was the optimal choice for our optimization process. In comparison to other optimization

algorithms, the Adam optimizer is superior in almost every respect. It operates more quickly and requires fewer tuning parameters. The binary cross-entropy logarithmic loss function was utilized since there are only two class variables. The network has a binarycross entropy loss with a batch size of 32 for 40 epochs. The parameters of the models applied are given in Table I.

D. Model compression

It is necessary to deploy the trained models on the edge device once they have been trained. This stage necessitates the reduction of the model's overall size. Because of its reduced size, the model requires less storage space on the user's device. It decreases the amount of RAM that is used and the amount of time that is spent inference. Furthermore, the decrease in latency via the lowering of inference time has an influence on the power consumption of the device. When TensorFlow Lite is used, the following advantages may be realized: The TensorFlow Lite converter accepts a TensorFlow model and creates a TensorFlow Lite model in an optimized FlatBuffer format with the file extension.tflite Fig. 3. Google created the very efficient and portable FlatBuffer format.

```
converter = tf.contrib.lite.TFLiteConverter.from_saved_model(history_eff)
tflite_model = converter.convert()
open("model.tflite", "wb").write(tflite_model)
```

Fig. 3. TensorFlow Lite Code for conversion.

This format offers a number of benefits beyond TensorFlow's protocol buffer model format, including reduced size and quicker inference. This enables TensorFlow Lite to function more effectively on systems with low computing and memory resources. Our model was saved as a tflite file after it was changed to TensorFlow lite.

IV. Application Development

These are the two stages of supervised machine learning, which are training and inference. It is challenging to use a mobile device for machine learning since the training process might be computationally costly and take weeks or months to finish. We were able to solve this difficulty by using a powerful computer for training and a mobile device for inference Fig. 4 . Melanlysis, is an Android application that was developed using the Java programming language using the Android Studio platform. We have utilized the OpenCV library to implement the camera functionality in order to keep things as simple as possible. Real-time image processing using a camera is made possible by the OpenCV open-source library, which is available for free.

It is used to perform a variety of image processing functions, such as image capture, and was created with a heavy emphasis on real-time application performance in mind. In order to make the pretrained model available on the Android platform, the. tflite file has been uploaded. After launching the program,

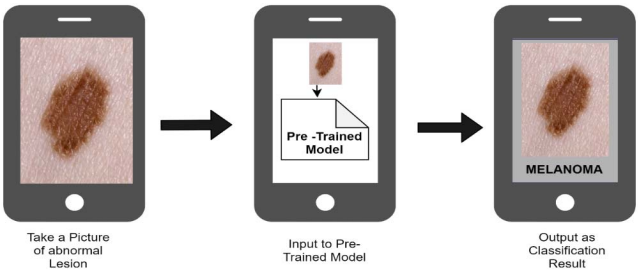

Fig. 4. Application Development Overview.

the user will take a photo of the suspicious lesion. The pre-trained model will then be tested on the application and the classification result will be shown.

A. TFLite Model Deployment

As shown in Fig. 5, TensorFlow Lite is a tool package that makes it possible to do on-device deep learning [44]. This allows us to integrate the deep learning models that we have trained into an Android application. The integration technique is responsible for transferring the machine learning model to mobile devices. TensorFlow Lite can operate successfully on devices with limited computation and memory resources as a consequence of this, which has a variety of advantages, including smaller model sizes and faster inference. [45] To make the pre-trained model compatible with the mobile application, we need to make certain modifications to it. In this study, we used the Python library TensorFlow Lite Converter [44]to convert our pre-trained model to the.tflite format. The results were impressive.

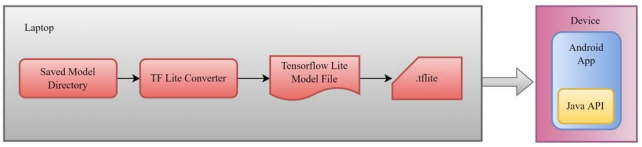

Fig. 5. TFLite Model Deployment

V. Evaluation

A. Experimental setup

In order to implement all of the models, the Python programming language and the TensorFlow library were employed. In order to carry out all of these tests, the kaggle notebook platform was used. Kaggle is a virtual environment that may be accessed over the internet. The dataset that we utilized for our approach has already been released in the Kaggle environment before we started working on it. We uploaded the data to the environment in the form of CSV files, which included the images in JPEG format.

B. Dataset

Many datasets about melanoma can be obtained online to assist in the development of computer-aided diagnosis-related

work. Using the dermoscopic image collection ISIC (2020) dataset, we have developed our mobile deep learning for melanoma identification [46]. A high-quality magnifying lens and a well-illuminated setting are used to acquire photos for the dermoscopic image dataset. A total of 44,108 photos are included in the dataset, which includes 33,126 training images and 10,982 test images Fig. 6 . Only a very small proportion, 1.7 percent, of the 33,126 skin lesion samples collected from 2,056 individuals had malignant melanoma, The ground truth data is given for the training set and test set , and includes the following information : patient ID, lesion ID, gender, estimated age, anatomical location, diagnosis, and whether the lesion is benign or malignant.

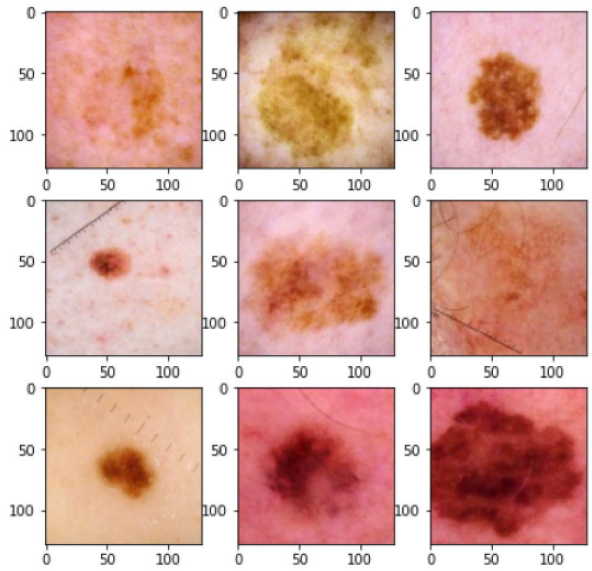

Fig. 6. Random Images From Dataset.

C. Evaluation Metrics

The accuracy, sensitivity, F1 score, and specificity metrics of the network are used to assess the network's overall performance. When doing a classification task, the best border between classes is utilized to predict the classifications of the data to be processed. By comparing the accuracy, sensitivity, and specificity numbers, it is possible to determine the ideal border. When determining the competency of an approach to calculate the precise significance, accuracy is used. The true positive rate, also known as sensitivity, is a measure of the number of malignant melanoma pictures that were accurately diagnosed as malignant. A measure of specificity, also known as the true negative rate, is the proportion of benign melanoma pictures that are accurately diagnosed as benign. A classification approach with high accuracy(5), sensitivity(2), F1 score(4), and specificity(3) value suggests that it is effective. All of those parameters are calculated using the terms true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) respectively. Where,

$$Sensitivity = (\frac{TP}{TP+FN}) \tag{2}$$

$$Specificity = (\frac{TN}{FP+TN}) \tag{3}$$

$$F1score = (\frac{2TP}{2TP+FP+FN}) \tag{4}$$

$$Accuracy = (\frac{TP+TN}{TP+FP+FN+TN}) \tag{5}$$

D. Experimental Result

From the beginning of training Fig. 7, the accuracy of the Melanlysis and EfficientNet Lite-0 model was quite high and stable, and in the validation period, it continued to be stable. On the other hand, in both situations, the MobileNet V2 and Resnet-50 model's accuracy was at the bottom, and with the increasing number of epochs, the accuracy went high.

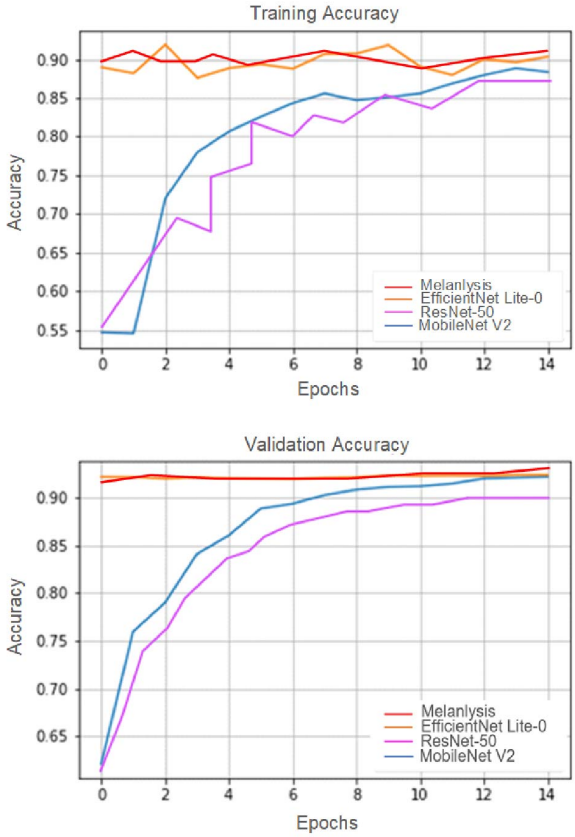

Fig. 7. Comparative Accuracy /Epochs .

From Fig. 8, the model loss with increasing epochs is also shown. We noticed fluctuating train loss, while the validation loss steadily decreases at epoch 14 for Melanlysis and Efficient Net-Lite-0 model. On the other hand, the train losses steadily decrease and, while the validation loss suddenly decrease at epoch 2 for MobileNet V2 and ResNet-50 model.

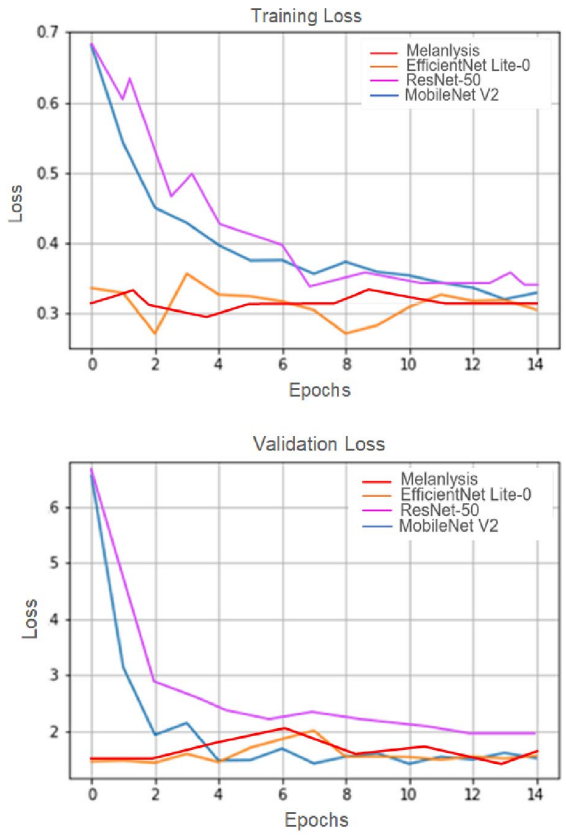

Fig. 8. Comparative Loss /Epochs .

(Table II) illustrate the comparative accuracy, sensitivity, specificity, and F1 score values of EfficientNetLite-0 and MobileNet V2.It can be clearly shown, that the EfficientNetLite-0 model outperformed the MobileNet V2 model on the concern of effectiveness.

TABLE II
COMPARISON BETWEEN ALL MODELS

Criterion	Melanlysis	EfficientNet-lite0	MobileNetV2	ResNet-50
Accuracy	94%	93.2%	93%	90%
Sensitivity	92.5%	92.5%	92.7%	89.4%
Specificity	89.5%	88.5%	88.5%	88%
F1-Score	93%	92.5%	92.1%	90%

E. Melanlysis Application

Melanlysis , The Android application's primary objective was to make things as simple as possible for the user to go through. In order for the application to function, it should be as follows: Fig. 9 . In order to begin, you must first launch the application, and the suspicious skin lesion should be photographed. To classify a picture, just need to press a single button. In the application, run the detection algorithm on a picture using the pre-trained model that was previously created. The user is then presented with the most relevant category on the screen, as well as the accuracy with which the classification was made.

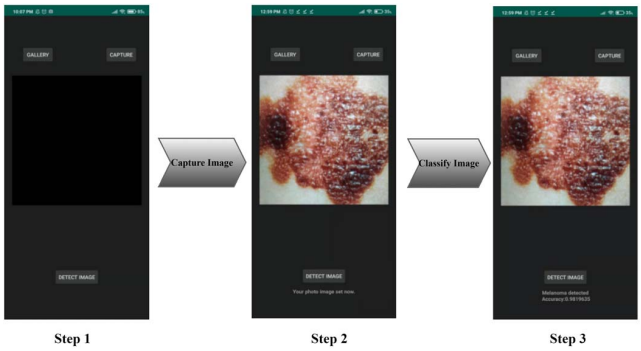

Fig. 9. Melanlysis Interface and Workflow.

Latency is the time required to perform a single inference using a given model.When it comes to specific applications, such as those that include real-time prediction, this response time is absolutely necessary. Since it is not dependent on any hefty server or cloud, there is no need to make a return trip to the server and there is no need to wait for the results to be returned. The application is capable of quickly classifying new data. The storage size of the Melanlysis is 23.18MB . Since the application code is written in Java, we calculate the latency of the application by using the TimingLogger class in Java. This class is used to capture the execution time measurement. To begin, we simply create a new instance of the TimingLogger class and then call out to the addSplit(split-label) method for the code that we want to measure, starting from taking the image as input and showing the output result that we want to measure. Then we call dumpToLog() to get the execution time of the application. The latency of the application is .10 ms.

VI. CONCLUSION

According to the findings of this research, we have developed a deep convolutional neural network for melanoma image classification that is based on a mobile device. We utilized the open source dermosocopic image collection entitled the SIIM ISIC 2020 dataset, which was created by the International Skin Imaging Collaboration (ISIC) and is available for download for free online . It comprises a total of 44,108 photos, including 33,126 training images and 10,982 test images in total. Because the dataset was unbalanced, we decided to use the data augmentation approach. We illustrate the use of WGAN for data augmentation. To evaluate our proposed model, we implemented three deep learning algorithms: EfficientNet-lite 0, MobileNet V2, and ResNet-50 , all of them are very efficient for mobile applications due to their small size and low memory requirements. The Melanlysis model outperformed all of the existing models in terms of accuracy, with a 94% accuracy rating. The TensorFlow Lite framework was used to port the model to the Android app "Melanlysis." By using the TensorFlow Lite converter, the Melanlysis was converted into a .tflite file and deployed in the application. When the app

was tested on an unknown library of images, it was able to correctly find lesions.

VII. Limitation and Future work

In our method, one of the most significant downsides is the difficulty in updating the pre-trained model, which is caused by the integration of the offline model into the application. For the application to enhance its categorization performance by retraining its model with more skin photos, it would be essential for the user to download and install the updated version, which would be troublesome and take a lot of time for the user. We only used the dermoscopic image dataset in this research since the program works better on dermoscopic photographs than it does on clinical photos, and hence we did not include any clinical images in our analysis.

We will explore the performance of the ensemble learning algorithm in the context of mobile deep learning applications. In machine learning, ensemble learning refers to a generic meta-approach that aims to improve predictive performance by aggregating predictions from many models. After that, we will train the model by combining multiple mobile deep learning models together. Increasing the dataset size by collecting extra-high-quality dermoscopic pictures from diagnostic centers and hospitals, or by merging patient information with the images, are examples of improvements. It is possible to construct a combined dataset using dermoscopic and clinical images. In the application section, we will include additional beneficial functions linked to skin cancer prevention, such as a recommendation to contact a doctor, a reminder to check the body, and notifications, among other things. It is being developed for both side effects and for both dermatologists and patients. The program allows for communication between the patient and the dermologists.

Acknowledgment

This research was supported by the Natural Science Foundation of Ningbo and the Key RD Project of Jiangsu Province (fund number: 202003N4057, BE2020665).

References

[1] Skin cancer statistics,https://www.wcrf.org/dietandcancer/cancer-trends/skin-cancer-statistics.[Accessed Feb, 2022].

[2] Cancer Council Australia. Understanding skin cancer - a guide for people with cancer, their families and friends, 2018. https://www.cancer.org.au/about-cancer/ types-of-cancer/skin-cancer.html .[Accessed Feb, 2022].

[3] Canadian Cancer Society's Advisory Committee on Cancer Statistics. Canadian cancer statistics 2014 - special topic: Skin cancers, 2014. https://www.cancer.ca/statistics. [Accessed Feb, 2022].

[4] Siegel, R. L., Miller, K. D., Jemal, A. (2019). Cancer statistics, 2019. CA: a cancer journal for clinicians, 69(1), 7-34.

[5] Cancer Facts and Figures. American Cancer Society. https://www.cancer.org/content /dam/cancer-org/research/cancerfacts-and-statistics/annual-cancer-facts-and figures/2020/cancer-factsand-figures-2020.pdf. [Accessed Feb, 2022].

[6] Global Cancer Observatory ,https://gco.iarc.fr/tomorrow/ [Accessed Feb, 2022].

[7] Ferlay, J., Steliarova-Foucher, E., Lortet-Tieulent, J., Rosso, S., Coebergh, J. W. W., Comber, H., ... Bray, F. (2013). Cancer incidence and mortality patterns in Europe: estimates for 40 countries in 2012. European journal of cancer, 49(6), 1374-1403.

[8] "Cancer Facts and Figures 2021," American Cancer Society, Available: https://www.cancer.org/content/dam/cancer-org/research/cancer-facts-and-statistics/annual-cancer-facts-and-figures/2021/cancer-facts-and-figures-2021.pdf, [Accessed Feb, 2022].

[9] "Key Statistics for Melanoma Skin Cancer," American Cancer Society, Available: https://www.cancer.org/cancer/melanoma-skin-cancer/about/key-statistics.html, [Accessed Feb, 2022].

[10] Al-Masni, M. A., Kim, D. H., Kim, T. S. (2020). Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification. Computer methods and programs in biomedicine, 190, 105351.

[11] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Skin cancer classification using deep learning and transfer learning," in Proc. 9th Cairo Int. Biomed. Eng. Conf. (CIBEC), Dec. 2018, pp. 90..93.

[12] S. Gulati and R. K. Bhogal, "Detection of malignant melanoma using deep learning," in Proc. Int. Conf. Adv. Comput. Data Sci. Singapore: Springer, Apr. 2019, pp. 312..325.

[13] [13] Jianu, S. R. S., Ichim, L., Popescu, D. (2019, March). Automatic diagnosis of skin cancer using neural networks. In 2019 11th International Symposium on Advanced Topics in Electrical Engineering (ATEE) (pp. 1-4). IEEE.

[14] Warsi, F., Khanam, R., Kamya, S., Suárez-Araujo, C. P. (2019). An efficient 3D color-texture feature and neural network technique for melanoma detection. Informatics in Medicine Unlocked, 17, 100176.

[15] Khan, M. A., Javed, M. Y., Sharif, M., Saba, T., Rehman, A. (2019, April). Multi-model deep neural network based features extraction and optimal selection approach for skin lesion classification. In 2019 international conference on computer and information sciences (ICCIS) (pp. 1-7). IEEE.

[16] Abbas, Q., Celebi, M. E. (2019). DermoDeep-A classification of melanoma-nevus skin lesions using multi-feature fusion of visual features and deep neural network. Multimedia Tools and Applications, 78(16), 23559-23580.

[17] Wang, Y., Pan, H., Yang, B., Bian, X., Cui, Q. (2019, September). Mutual learning model for skin lesion classification. In International Conference of Pioneering Computer Scientists, Engineers and Educators (pp. 214-222). Springer, Singapore.

[18] Nida, N., Irtaza, A., Javed, A., Yousaf, M. H., Mahmood, M. T. (2019). Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering. International journal of medical informatics, 124, 37-48.

[19] Lopez, A. R., Giro-i-Nieto, X., Burdick, J., Marques, O. (2017, February). Skin lesion classification from dermoscopic images using deep learning techniques. In 2017 13th IASTED international conference on biomedical engineering (BioMed) (pp. 49-54). IEEE.

[20] Ge, Y., Li, B., Zhao, Y., Guan, E., Yan, W. (2018, February). Melanoma segmentation and classification in clinical images using deep learning. In Proceedings of the 2018 10th international conference on machine learning and computing (pp. 252-256).

[21] Namozov, A., Im Cho, Y. (2018, October). Convolutional neural network algorithm with parameterized activation function for melanoma classification. In 2018 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 417-419). IEEE.

[22] Yu, Z., Jiang, X., Zhou, F., Qin, J., Ni, D., Chen, S., ... Wang, T. (2018). Melanoma recognition in dermoscopy images via aggregated deep convolutional features. IEEE Transactions on Biomedical Engineering, 66(4), 1006-1016.

[23] Yang, J., Xie, F., Fan, H., Jiang, Z., Liu, J. (2018). Classification for dermoscopy images using convolutional neural networks based on region average pooling. IEEE Access, 6, 65130-65138.

[24] Li, Y., Shen, L. (2018). Skin lesion analysis towards melanoma detection using deep learning network. Sensors, 18(2), 556.

[25] Hagerty, J. R., Stanley, R. J., Almubarak, H. A., Lama, N., Kasmi, R., Guo, P., ... Stoecker, W. V. (2019). Deep learning and handcrafted method fusion: higher diagnostic accuracy for melanoma dermoscopy images. IEEE journal of biomedical and health informatics, 23(4), 1385-1391.

[26] Albahar, M. A. (2019). Skin lesion classification using convolutional neural network with novel regularizer. IEEE Access, 7, 38306-38313.

[27] Hasan, M., Barman, S. D., Islam, S., Reza, A. W. (2019, April). Skin cancer detection using convolutional neural network. In Proceedings of the 2019 5th international conference on computing and artificial intelligence (pp. 254-258).

[28] Albert, B. A. (2020). Deep learning from limited training data: Novel segmentation and ensemble algorithms applied to automatic melanoma diagnosis. IEEE Access, 8, 31254-31269.
[29] Almaraz-Damian, J. A., Ponomaryov, V., Sadovnychiy, S., Castillejos-Fernandez, H. (2020). Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures. Entropy, 22(4), 484.
[30] Hameed, N., Shabut, A. M., Ghosh, M. K., Hossain, M. A. (2020). Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques. Expert Systems with Applications, 141, 112961.
[31] Zhang, N., Cai, Y. X., Wang, Y. Y., Tian, Y. T., Wang, X. L., Badami, B. (2020). Skin cancer diagnosis based on optimized convolutional neural network. Artificial intelligence in medicine, 102, 101756.
[32] Hasan, M. K., Dahal, L., Samarakoon, P. N., Tushar, F. I., Martí, R. (2020). DSNet: Automatic dermoscopic skin lesion segmentation. Computers in Biology and Medicine, 120, 103738.
[33] Pour, M. P., Seker, H. (2020). Transform domain representation-driven convolutional neural networks for skin lesion segmentation. Expert Systems with Applications, 144, 113129.
[34] Abayomi-Alli, O. O., Damasevicius, R., Misra, S., Maskeliunas, R., Abayomi-Alli, A. (2021). Malignant skin melanoma detection using image augmentation by oversampling in nonlinear lower-dimensional embedding manifold. Turkish Journal of Electrical Engineering Computer Sciences, 29(SI-1), 2600-2614.
[35] Hosny, K. M., Kassem, M. A., Fouad, M. M. (2020). Classification of skin lesions into seven classes using transfer learning with AlexNet. Journal of digital imaging, 33(5), 1325-1334.
[36] Kassem, M. A., Hosny, K. M., Fouad, M. M. (2020). Skin lesions classification into eight classes for ISIC 2019 using deep convolutional neural network and transfer learning. IEEE Access, 8, 114822-114832.
[37] Maier, T., Kulichova, D., Schotten, K., Astrid, R., Ruzicka, T., Berking, C., Udrea, A. (2015). Accuracy of a smartphone application using fractal image analysis of pigmented moles compared to clinical diagnosis and histological result. Journal of the European Academy of Dermatology and Venereology, 29(4), 663-667.
[38] Thissen, M., Udrea, A., Hacking, M., von Braunmuehl, T., Ruzicka, T. (2017). mHealth app for risk assessment of pigmented and nonpigmented skin lesions—a study on sensitivity and specificity in detecting malignancy. Telemedicine and e-Health, 23(12), 948-954.
[39] Jaworek-Korjakowska, J., Kleczek, P. (2018). Eskin: study on the smartphone application for early detection of malignant melanoma. Wireless Communications and Mobile Computing, 2018.
[40] Tajeddin, N. Z., Asl, B. M. (2018). Melanoma recognition in dermoscopy images using lesion's peripheral region information. Computer methods and programs in biomedicine, 163, 143-153.
[41] Dai, X., Spasić, I., Meyer, B., Chapman, S., Andres, F. (2019, June). Machine learning on mobile: An on-device inference app for skin cancer detection. In 2019 Fourth International Conference on Fog and Mobile Edge Computing (FMEC) (pp. 301-305).IEEE
[42] Phillips, K., Fosu, O., Jouny, I. (2015, April). Mobile melanoma detection application for android smart phones. In 2015 41st Annual Northeast Biomedical Engineering Conference (NEBEC) (pp. 1-2). IEEE.
[43] Ioffe, S., Szegedy, C. (2015, June). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International conference on machine learning (pp. 448-456). PMLR.
[44] https://www.tensorflow.org/lite/guide [Accessed: Feb, 2022]
[45] https://www.tensorflow.org/lite/convert/index [Accessed: Feb, 2022]
[46] Rotemberg, V., Kurtansky, N., Betz-Stablein, B., Caffery, L., Chousakos, E., Codella, N., ... Soyer, H. P. (2021). A patient-centric dataset of images and metadata for identifying melanomas using clinical context. Scientific data, 8(1), 1-8.