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# *Lightweight Fingerprint Classification Using EfficientNet on the Edge Impulse Platform*

**Sinan Liu**

*School of Computer Science and Engineering, University of New South Wales, Sydney, Australia*
*z5657776@ad.unsw.edu.au*

***Abstract.*** Fingerprint shape identification holds an important function in biological feature verification, crime detection, and entrance permission management. Traditional classify methods which are based on the Henry system heavily depend on manual feature picking, therefore this limits both accuracy and efficiency. Although Convolution Neural Networks (CNNs) have obvious promotion on fingerprint classification effect, many current models have the problem of high computation expense, especially when facing large-scale identification situations. For solving this problem, this article puts forward a light fingerprint type classification method which combines the Henry classification frame and neural networks based on EfficientNet, and it is realized by the Edge Impulse platform. The original five Henry categories are combined into three main groups: arch, loop, whorl, therefore the matching scope is cut to around one-third of the original data collection. Experiments which are carried out on the public NISTDB4 dataset have shown that the method this paper puts forward obtains classification accuracy from 93.72% to 97.98% in different EfficientNet variants (B0 to B5). The B5 model can give the biggest accuracy of 97.98% with 28.3 million parameters and 25.4 MB flash use, thus providing a good balance between effect and resource cost. Further analysis upon errors makes clear that blurry images, noise pollution, and unclear patterns are the main reasons for errors. On the whole, the method this paper puts forward gives an effective, usable resolution for fingerprint shape identification in environments with limited resources.

***Keywords:*** Fingerprint recognition, computer vision, image classification, edge impulse.

## 1. Introduction

Fingerprint type distinguishing is a basic biometric technique for automatic individual recognition [1]. Because of its special character and long-period stability, this technology is broadly used in the verification of identity, investigation of crimes and control of safety. In the late period of 19th century, the Henry Classification System was created as one method of fingerprint classification, in which fingerprints are divided on foundation of the macroscopic characteristics of fingerprint patterns, for example, the position relation between ridges and deltas. In this system, fingerprint is divided into five big kinds: arch (A), tented arch (T), left loop (L), right loop (R), and whorl (W). Although this system undertook an important function in the early phase of fingerprint

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identification, its great dependence on manpower hence brought about restricted accuracy and efficiency.

The tradition fingerprint shape recognition methods which based on Convolution Neural Networks (CNNs) normally have two stages: fingerprint picture pre-handling and personal identity matching. But the current fingerprint type classification methods still leave space for promotion in calculation efficiency, especially on large-scale recognition occasions, where direct one-to-many matching produces huge calculation expenses.

In the last years, researches on classification which is based on CNN have more and more put emphasis on model lightweight making, attention mechanisms, and multi-modal mixing, therefore to decrease calculation complexity, meanwhile keeping similar classification effect. In the field of light weight architecture design, typical works like MobileNetV3 done by Howard [2,3], and EfficientNet done by Tan have obtained very big progress [4]. These light-weight neural network structure constructions, which possess effective model design, small calculation expenditure, and quick reasoning, have further promoted the usage of Automatic Machine Learning (AutoML), therefore making hyperparameter adjustment and model arrangement not so much work-consuming.

Although some researches have discussed fingerprint classification with more pattern kinds [5-7], their models are frequently designed by hand, thus this makes it hard to reach the best performance. Automatic Machine Learning, hence, gives a valid method through automatically dealing with model choice and carrying out the optimization on hyperparameters.

This article puts forward a classification method which combines the Henry Classification System together with lightweight neural networks, in order to let computational cost be minimized while classification accuracy is still kept. In the method which this paper puts forward, after the input data is preprocessed, fingerprints are divided into three big kinds: arch (A), loop (L), and whorl (W). In the actual situation of the real world, the patterns of fingerprints can be further divided into categories that have more fine grains. In order to make classification granularity and computational efficiency reach a balance, the five Henry pattern categories are merged into three main classes, which are arch (A), loop (L), and whorl (W), wherein arch and tented arch are combined to be class A, therefore left and right loops are combined to be class L. Experiment outcomes indicate that this layered classification method greatly lowers calculation expenses through reducing the matching range to about one third of the original data set, hence it does not make the whole classification performance become worse.

## 2. Method

### 2.1. Dataset preparation

The experiments of this research are carried out on the public NISTDB4 fingerprint data set [8], which has been widely utilized in former fingerprint classification and recognition research works. After merging the original categories, the dataset that obtained contains three main kinds of patterns: arch (A), loop (L), and whorl (W). On the whole, The data collection holds about 2,400 fingerprint gray level pictures which have a resolution of 512×512 picture elements. To speak specifically, among these samples, 801 samples belong to class A, 801 samples belong to class L, and 799 samples belong to class W, therefore this causes a class distribution that is nearly balanced. And just in this research, the data set is randomly split to a training set (1,922 pictures) and a testing set (478 pictures). The representative samples are respectively displayed in Figure 1.

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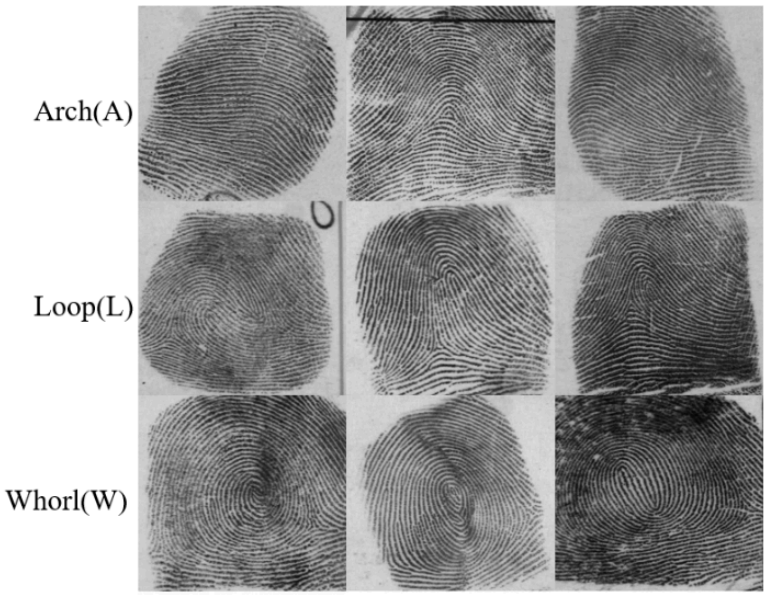



Figure 1. Sample fingerprint images [8]

## 2.2. Edge impulse-based CNN for fingerprint pattern classification

### 2.2.1. Convolutional neural network

Convolutional neural networks have become a standard choice for image classification because they can automatically learn discriminative features directly from raw images [9]. Being different from hand-made characteristics, CNNs carry out optimization of feature extraction and classification in a joint way, which therefore often promotes the robustness toward deformation and noise. In this research work, a classifier which is based on CNN is trained, for mapping every 512×512 grayscale fingerprint image to one among three main pattern classes. The learned characteristics catch both pattern minutiae and overall structures, therefore permitting dependable division among arch, loop, and whorl groups.

### 2.2.2. Edge impulse

Edge Impulse is one platform which is based on cloud for machine learning operations (MLOps) [10,11], it is used for developing embedded and Tiny ML systems that are able to be deployed to many kinds of hardware targets.

For lowering the manual work in model design and training setting, this research utilizes Edge Impulse as one automatic machine learning platform to construct, train, and put the fingerprint pattern classifier into use. The labeled fingerprint pictures are inputted into an Edge Impulse project, and this platform offers a full working flow that includes dataset management, model training and performance monitoring. In this research, the work utilizes the transfer learning provided by Edge Impulse, which permits effective parameter adjustment of a pre-trained model on the target fingerprint data set. This platform-based working flow avoids massive try-and-guess when choosing framework structures and adjusting super parameters, therefore it can give out a usable model that is fit for high-efficiency reasoning calculation.

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### 2.2.3. EfficientNet

EfficientNet is a kind of CNNs which puts emphasis on the balance between accuracy and efficiency by way of compound scaling [3]. Instead of adjusting depth, width, or resolution one by one, it enlarges all three dimensions at the same time by employing a unified method. In the Edge Impulse platform, EfficientNet has several different editions, which are from B0 to B5, and this classification is based on the model's dimension and the quantity of parameters. In general speaking, B0 is the version that has smallest size and fastest running speed, while B5 is a thing that is much bigger and possesses more complex structure. When the quantity goes up from 0 to 5, the model becomes more "clever" and more exact, therefore it possesses more layers, hence it can process images with higher resolution. However, this therefore also means that it has the requirement of more memory and longer time. Through combining the lightweight design of EfficientNet with transfer learning, the classifier that this paper gets is still computationally efficient, therefore it can keep accuracy in large-scale identification work.

### 2.2.4. Model procedures

Figure 2 carries out the summary of the whole working flow of the method this paper puts forward. Firstly, each input fingerprint image is carried out preprocessing and is kept at the original 512×512 grayscale resolution. Second, the marked training set is utilized on the Edge Impulse platform to carry out fine adjustment for an EfficientNet-based sorter by means of transfer learning, thus generating a three-class pattern prediction device. Third, the model that has been trained is assessed upon the testing set by utilization of overall accuracy, and moreover memory occupation and time consumption. At the last, the model which already finished training can be exported out from Edge Impulse, and be deployed to carry out inference on local machine or the device itself.

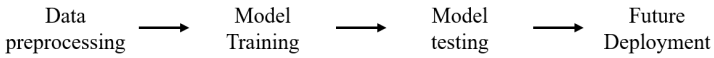



Figure 2. The overall workflow of the experiment (picture credit: original)

## 3. Results and discussion

The whole performance is carried out summary in Table 1. Inference time is the time which the model needs to spend for getting the output done. Flash Usage is spoken of as the quantity of storage which the model uses within flash memory.

### 3.1. Model performance

For evaluating whether the put-forward fingerprint classification method has good effect, six EfficientNet transformed models (B0 to B5) have been trained and tested on the NISTDB4 dataset in the same preprocessing and platform situation. Table 1 makes a summary of the performance target indexes, including parameter quantity, calculation time, memory usage, and classification correct rate.

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Table 1. Overall performance

| Model Type | Parameter count | Inferencing Time (s) | Flash Usage (MB) | Accuracy (%) |
|---|---|---|---|---|
| B0 | 4M | 1285 | 4.7 | 93.72% |
| B1 | 6.5M | 1889 | 7.5 | 95.19% |
| B2 | 7.7M | 2491 | 8.8 | 94.35% |
| B3 | 10.7M | 2994 | 12.0 | 96.23% |
| B4 | 17.5M | 3489 | 18.3 | 97.11% |
| B5 | 28.3M | 4011 | 25.4 | 97.98% |

According to what Table 1 shows, all models reach accuracy that is higher than 93%, the smallest model (B0) achieves 93.72% when it only uses 4 million parameters and 4.7 MB of flash memory. This hence proves that even the extremely lightweight neural networks are able to carry out effective work on three-class fingerprint pattern classification. Along with the increment of model complexity from B0 to B5, both the accuracy and the consumption of resources go up thusly. The B5 model has obtained the top accuracy of 97.98%, but it needs 28.3 million parameters and 25.4 MB of flash memory, hence the inference time arrives at about 4011 seconds for each image.

It is worth pointing out that the B3 model obtains an accuracy of 96.23% by only possessing 10.7 million parameters and 12.0 MB flash memory usage, thus it provides a good balance between performance result and resource use efficiency. By way of opposition, the B2 model displays a small accuracy decrease (94.35%) when compared with B1 (95.19%), this may be ascribed to structure differences or not best fine-tuning settings under the Edge Impulse AutoML pipeline. On the whole, the outcomes show that the hierarchical classification method this paper puts forward (arch, loop, whorl) can effectively decrease matching complexity, at the same time as it keeps accuracy that has competitive strength.

## 3.2. Error analysis

Although the models that this paper puts forward obtain satisfying accuracy, some wrong classification cases still remain. The deep reasons can mainly be divided into three kinds: unclear images, images polluted by noise and unclear pattern images.

### 3.2.1. Blurry sample anaysis

Blurry pictures shown in Figure 3 make up the main origin of classification mistakes. Motion-caused blurring or out-of-focus blurring greatly reduces the identifiability of ridge flow shapes and detail points, both of which are necessary for correct fingerprint identification. Under these circumstances, the neural network cannot stably pick up local ridge features, for example branching points and ridge endpoints, hence it causes confusion between fingerprint categories that have alike structures. For instance, a fuzzy loop-shape fingerprint can by mistake be categorized as an arch hence the disappearance of curvature information. For easing this problem, image sharpening or deblurring pre-treatment methods can be utilized.

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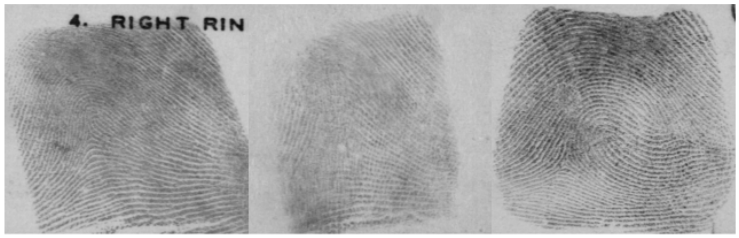



Figure 3. Blurry samples [8]

### 3.2.2. Noise-contaminated sample analysis

Images which are polluted by noise are fingerprint samples that are degraded by many kinds of noise shown in Figure 4, which include dry skin, moisture, oil remainders, or sensor artificial products. These pollutant materials bring about false structures or break the real ridge connecting situation. As a consequence, the neural network might by mistake treat noise as valid small details or ignore existing ridge characteristics. For an example, the dispersed bright points which come from dirt can imitate the minutiae points, therefore leading to wrong classification of sorts. The utilization of adaptive histogram equalization or Gabor filtering is able to assist in the reduction of the negative influence of this kind of noise.



Figure 4. Noise-contaminated samples [8]

### 3.2.3. Ambiguous pattern sample analysis

Some fingerprint pictures themselves in nature contain ridge shapes that at the same time show features of two or more standard fingerprint categories shown in Figure 5. This kind of ambiguity does not come from image quality drop, but comes from the natural shape structure of the fingerprint itself. For instance, a fingerprint can have a loop-shaped core area and at the same time it can present whorl-shaped concentric lines in the outer part. When these mixed type characteristics exist, the neural network has difficulty in deciding the main category, therefore it often generates a classification result which only matches a part of the evidences. This kind of mistake has more inner nature, hence it may need soft-label training or hierarchical classification methods to solve.

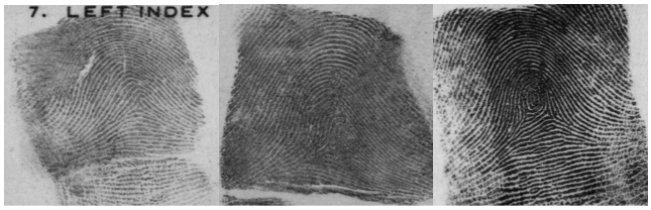



Figure 5. Ambiguous pattern samples [8]

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## 4. Conclusion

This paper put forward a fingerprint figure classification method which combines the Henry Classification System with light weight convolutional neural networks, and it is realized through the Edge Impulse platform. The method this paper puts forward cuts the matching range to about one third of the initial data set, thus greatly decreasing calculation expenses without reducing classification exactness. Experiment outcomes on the NISTDB4 data collection have proven that the classifiers which are based on EfficientNet reach accuracy that lies from 93.72% to 97.98%, hence the B5 model provides the best balance between accuracy (97.98%) and resource use (28.3M parameters, 25.4 MB flash memory occupation). The analysis of errors discovers that wrong classifications mainly come from images that are not clear, pollution by noise, and fingerprint patterns which themselves have ambiguity. In the future, work that researchers will carry out shall place focus on bringing in image preprocessing methods like deblurring and adaptive filtering for easing these problems, and therefore also on searching hierarchical classification tactics for better dealing with ambiguous patterns. On the whole, the method this paper puts forward proves that light-weight neural networks which are combined with automatic machine learning can provide a solution that is high-efficiency and can be deployed for the identification of fingerprint patterns in scenes where resources are limited.

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