FINGER KNUCKLE PRINT CLASSIFICATION USING PRETRAINED VISION MODELS

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***Abstract*—Privacy and security are significant issues in the field of biometric traits in today's world. This research paper presents a comprehensive study that utilizes seven different deep learning models to classify Finger Knuckle Prints (FKP). The main aim of this study is to examine the efficacy of fine-tuning pretrained vision models in adapting to the specific dataset being analyzed. The models employed in this study include AlexNet, DensNet, EfficientNet, GoogleNet, Shallow Convolutional Neural Networks (SCNNs), ResNet50, and VisionTransformer. The models underwent training and testing procedures utilizing a comprehensive dataset obtained from 165 volunteers by Hong Kong Polytechnic University (Poly U). This dataset consisted of about 7,920 photos depicting the FKP gestures. A series of experiments were done to investigate the impact of alterations to the architectural design parameters of the models on the achievement of optimal recognition accuracy. The findings from our investigation indicate that the SCNNs and AlexNet had remarkably high accuracy rates of 98.3% and 96.224%, outperformed all other models. The accuracy rates reached by different models are as follows: EfficientNet achieved an accuracy rate of 98.176%, AlexNet achieved 96.224%, GoogleNet attained 95.601%, ResNet50 achieved 92.598%, DenseNet achieved 81.224%, and VisionTransformer gave the lowest accuracy of 79.513%.**

***Index Terms*—Finger Knuckle Print, Vision Models, AlexNet, DensNet, EfficientNet, GoogleNet, shallow Convolutional Neural Network, ResNet50, VisionTransformer.**

I. Introduction

Because of the widespread use of computers and the advent of the Internet, we now have easy access to information. As consumers become more concerned about security of their personal information, the user authentication mechanism is gaining popularity. The usage of alphanumeric usernames and passwords is the most frequent method of computer authentication. The conventional password authentication solutions are simple, but only if you know the password, because user authentication is vulnerable [1], [2]. According to [3], personal authentication is gaining attention in both academic and industrial research due to its numerous applications such as computer security, physical outlet control, law enforcement, and banking, among others.

Because of the high level of consumer acceptance, hand-based biometrics have received a lot of attention. Recently, the finger-knuckle-print (FKP) has entered the biometric family and been introduced for personal authentication [4], [5].

Woodard and Flynn were the first researchers to use the FKP in their work, creating a database with the Minolta 900/910 sensor [6]. Woodard's work have shown the FKP's superiority as a biometric. The limitations of the sophisticated capturing procedure, as well as sensor weight, cost, and size, limited the commercial application of this sensor. Later, as indicated in [3] an imaging system is developed that employs a digital camera focused against a white background under steady illumination to obtain the finger back surface. The captured images then preprocessed to evolve the finger knuckle zones, and then analysis methods like Principal component analysis (PCA), Linear discriminant analysis (LDA) and Incremental dynamic analysis (ICA) were combined to make feature evolving and matching. PCA, ICA and LDA are popular methods for feature extraction and dimension reduction [7]–[9]. The device is doomed to have a big size due to the sacrificially capturing of the whole hand back area.

Unlike the previous systems, which capture the images of the entire hand first and then evolve the finger or finger knuckle surface zones, the work in [3] simplifies the following preprocessing processes by imaging the knuckle zone of the finger instantly. As a result, the imaging system's size is significantly reduced, and its application is enhanced. The inherent FKP patterns can be clearly captured since the finger knuckle sags somewhat during acquisition, allowing the individual characteristics of the FKP to be extracted accurately.

Machine learning techniques and deep learning methods have been used to address the issue of personal authentication [10]. In [11] researchers provide a Biometric Authentication system based on deep learning techniques, in which the user's finger knuckle is used to improve system security. This model can detect an authorized user based on a dominant finger knuckle pattern using a Convolution Neural Network (CNN) and extract features that are optimally compared to training photos. CNN is widely used because it is proved to be very successful for large scale image classification [12], [13].

Rachid Chlaoua et al. used deep learning techniques to improve finger-knuckle-print identification system based on PCANet and SVM classifier in [14]. Their research proposes a novel methodology in which deep learning is used to develop a multi-modal biometric system based on images of FKP modalities whose features were extracted using principal component analysis Network (PCANet). PCA is used in the proposed structure to train two-stage filter banks, which are then followed by basic binary hashing and block histograms for clustering at feature vectors, which are then used as input for classification by a linear multiclass Support Vector Machine (SVM) [15], [16].

In another work deep neural networks were used with batch normalized CNN for Finger Knuckle Print recognition [17]. They proposed a batch normalized Convolutional Neural Network (CNN) architecture with data augmentation for FKP recognition. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning system that can take in an image, assign importance learnable weights and biases to different aspects/objects in the image, and differentiate one from the other [18]. When compared to other classification algorithms, a ConvNet requires substantially less preprocessing. While simple systems need hand-engineering of filters, ConvNets can learn these filters characteristics with appropriate training [12], [19].

In [20] authors added a step to preprocess FKP images and then feature extraction algorithm is applied to extract coefficients that will be used in the matching process.

Improved neural networks such as quantum neural network (QNN), wavelet neural network (WNN), and quantum wavelet neural network (QWNN) are utilized in the classification process to achieve higher accuracy and faster convergence. This study implements quantum computing (QC) in the framework of the FKP recognition system. It offers the advantages of low inexactness and rapid execution speed due to the use of the quantum superposition state theory. Classic and deep neural networks are significantly slow, often requiring thousands of repetitions to reach the final response with an improbable inaccuracy.To address these challenges, some academics have suggested models that incorporate artificial neural networks (ANNs) and quantum neural networks (QNNs) [21], [22].

The remainder of this paper is organized as follows: Section 2 introduces the applied classification models, section 3 presents the experimental results and discussions. Ans section 4 is the conclusions.

II. Methodology

The performance of the suggested model is evaluated through experiments conducted on a database provided by Poly U. The database was produced from a sample of 165 volunteers spanning various age groups who placed their fingers in front of the FKP acquisition device. Of the participants, 125 were male and the remaining individuals were female. In each of the two distinct sessions of FKP picture acquisition, a total of 6 images are acquired for each of the right index finger, right middle finger, left index finger, and left middle finger. Consequently, every participant contributed a total of 48 FKP photos. The database has a total of 7,920 FKP grayscale photos, which are associated with 660 unique fingers. The two sessions, during which the images were captured, were separated by an average time gap of 25 days [23]. Figure 1 depicts the device and a sample of a captured photograph that has undergone processing in order to extract the region of interest (ROI).

Fig. 1.a: (a)

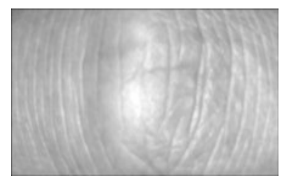

Fig. 1.b: (b)

Fig. 1: (a) Finger Knuckle acquisition device, (b) ROI, [23].

The models employed for retraining and evaluating the performance of our dataset are AlexNet, DensNet, EfficientNet, GoogleNet, SCNNs, ResNet-50, and VisionTransformer. The dataset is devided, where 80% is allocated for training and validation, a 5-fold cross-validation is performed, and the remaining 20% of the is designated as the testing set.

A. Shallow Convolution Neural Network

Shallow Convolutional Neural Networks are considered to be an earlier iteration in the progression of deep learning models utilized for the purpose of image recognition. While lacking the depth and complexity of contemporary competitors, shallow CNNs have played a crucial role in developing the discipline. During the initial years of the 1990s, Yann LeCun established the notion of CNNs by presenting the LeNet-5 design. The primary objective of this architecture was to facilitate the recognition of handwritten digits. Shallow CNNs often comprise a limited number of convolutional layers, which are then accompanied by pooling layers and fully connected layers. The primary focus of these networks lies in the acquisition of low-level properties, such as edges and textures. Although shallow CNNs may not possess the same level of depth and hierarchical feature extraction capabilities as deeper architectures such as ResNet or Inception, they have shown to be useful in performing image processing tasks by utilizing convolutional operations. The advantages of simplicity and efficiency are particularly notable in situations where there are constraints on computer resources or when addressing image recognition jobs that are relatively uncomplicated [24].

B. Transfer Learning

In the field of deep learning, it is imperative for the model to be exposed to a substantial volume of data during the training phase in order to acquire a greater depth of knowledge and proficiency. Deep transfer learning refers to the practice of utilizing preexisting deep learning models to train on a novel challenge. The primary objective of transfer learning is to identify common knowledge that may be effectively transmitted across different areas. In addition, appropriate methods are developed to facilitate the transmission of general knowledge [25]–[27]. Transfer learning consists of three main types: instance-based transfer, feature-based transfer, and shared parameter-based transfer. For a more comprehensive understanding of each strategy, please refer to [28]. In the classification system we have presented, pretrained models were utilized as a result of the substantial volume of data that necessitates significant computational resources for training purposes. The utilization of pretrained models has been found to expedite the learning process and result in time savings [25], [29].

1) AlexNet: The AlexNet model was developed by Alex Krizhevsky, Ilya Sutskever, and Geoffery Hinton. The model was trained using the ImageNet dataset, which consists of over 15 million labeled images with high resolution and covers 22,000 distinct classes. The model demonstrates a remarkable capacity to effectively and precisely categorize a vast collection of over 1.2 million photos. The AlexNet architecture leverages a graphics processing unit (GPU) to enhance the accuracy and efficiency of image categorization tasks. The neural architecture of AlexNet comprises a total of eight layers, which encompass five convolutional layers and three fully connected layers. The quantity of parameters amounts to 60 million, while the number of neurons reaches 650,000. Please refer to Figure 2 to see the architectural design of AlexNet. Overfitting is a common occurrence when working with larger datasets. To mitigate or minimize overfitting, researchers have employed a well-established regularization technique called dropout. Additionally, they have incorporated Rectified Linear Units (ReLU), overlapping pooling, and data augmentation as part of their approach [30]. The aforementioned characteristics of the AlexNet model were essential in securing its win in the 2012 ImageNet Large Scale Visual Recognition Competition (ILSVRC-2012), a yearly competition focused on image classification. In the realm of deep learning, AlexNet made a substantial contribution by propelling the research forward and showcasing the efficacy of convolutional neural networks (CNNs) in the domain of image classification tasks [31].

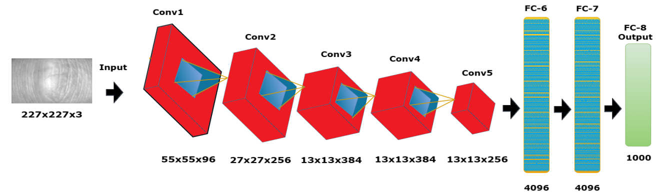

Fig. 2: Architecture of AlexNet model.

2) DenseNet: DenseNet, also known as Densely Connected Convolutional Networks, is a significant advancement within the realm of deep learning and CNNs. The architecture, proposed in 2017 by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger, was designed as a solution to address the challenges posed by the vanishing gradient problem and the inefficiencies observed in conventional CNN structures. In contrast to traditional CNNs, DenseNet establishes connections between each layer and every other layer in a densely connected manner. This architectural approach facilitates the reuse of features and enhances the flow of gradients across the network. The distinctive architecture of this structure not only facilitates the training of deep networks with a reduced number of parameters, but also promotes the flow of information, resulting in enhanced accuracy and generalization capabilities. DenseNet has densely connected building blocks, referred to as dense blocks, that effectively enable feature extraction and fusion. This characteristic renders DenseNet a resilient option for a range of computer vision applications, including but not limited to image classification, object identification, and segmentation [32]. The architectural structure of the model is depicted in Figure 3.

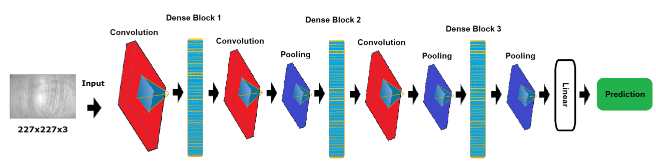

Fig. 3: Architecture of DenseNet model. This structure consists of three dense blocks, the layers between two adjacent blocks called transition layers through which the feature maps sizes are controlled.

3) EfficientNet: The EfficientNet model is a collection of deep neural networks designed to reduce the number of parameters required for training. This is achieved by the integration of many techniques, including convolutions, bottleneck blocks, depthwise separable convolutions, and squeeze-and-excitation modules. EfficientNet employs a predetermined set of scaling coefficients to uniformly scale all dimensions of depth, width, and resolution. The compound scaling strategy is justified by the need to accommodate larger input images, which necessitates the inclusion of additional layers to broaden the network's receptive field and an increased number of channels to effectively recognize more intricate patterns within the larger image [33]. The models are offered in several dimensions and are denoted as EfficieNet-B0, EfficieNet-B1, EfficieNet-B2, and so forth. The architectural design of EfficientNet is depicted in Figure 4. EfficientNet demonstrates reduced processing time and hence incurs lower computational expenses in comparison to alternative convolutional neural network (CNN) architectural models.

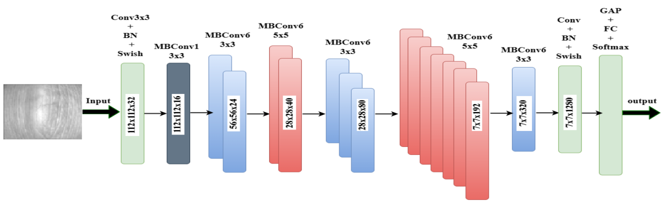

Fig. 4: Architecture of EfficientNet model.

4) GoogleNet: The Inception architecture, sometimes referred to as GoogleNet, is a noteworthy advancement in the progression of CNNs. It was created by researchers at Google in 2014. The GoogleNet, led by Christian Szegedy et al., was initiated to tackle the growing need for more complex and efficient neural networks in the field of image recognition. The distinguishing factor of GoogleNet was its inception modules, which provided a unique approach of including different filter sizes and parallel convolutions within a single layer. This design facilitated the network in capturing features at various dimensions and levels of abstraction, hence enhancing both accuracy and computational efficiency. The utilization of 1x1 convolutions for dimensionality reduction, which effectively reduces the number of parameters and processing cost, was popularized by GoogleNet. The primary characteristics of this model encompass the utilization of Inception modules, which have yielded remarkable outcomes in the ImageNet Large Scale Visual Recognition Challenge and have served as a source of inspiration for future architectures such as Inception-v2 and Inception-v3. The groundbreaking methodology employed by GoogleNet in its convolutional neural network (CNN) architecture has established a fundamental framework for deep learning models that are both highly efficient and precise. This influential technique has significantly impacted the advancement of cutting-edge models in the field of computer vision and beyond [34].

5) ResNet50: ResNet-50, also known as Residual Network-50, is a widely recognized convolutional neural network structure that has had a profound influence on the domain of deep learning, namely in the realm of computer vision applications. ResNet-50, a neural network architecture, was developed in a seminal publication by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015. The primary objective of this architecture was to tackle the difficulty of training neural networks with a large number of layers. The historical basis of this phenomenon may be traced back to the recognition that as networks increase in depth, they are more susceptible to encountering vanishing gradients, which impede the progress of training. In order to address this issue, ResNet-50 introduced the novel notion of residual blocks, which enabled the selective bypassing of specific layers. This architectural innovation facilitated the training of deep neural networks with enhanced efficacy. The ResNet-50 architecture is distinguished by its extensive sequence of residual blocks, resulting in a total depth of 50 layers. The primary characteristic of this architectural design is the inclusion of skip connections within each block, which facilitates the network's ability to capture intricate features while simultaneously ensuring fast gradient movement. The innovative architecture of ResNet-50 has established it as a fundamental model in the fields of image classification, object recognition, and image segmentation. It has continually demonstrated exceptional performance in a wide range of computer vision applications, consistently surpassing previous benchmarks and achieving the highest levels of accuracy and effectiveness [35]. The architecture of the model is shown in Figure 5.

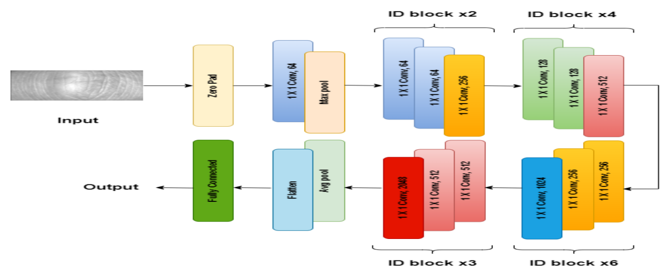

Fig. 5: Architecture of ResNet50 model.

6) VisionTransformer: The VisionTransformer (ViT) employs a distinct approach compared to the traditional design of CNNs for the purpose of image classification. The architectural design of ViTconsists of two main elements: a patch embedding layer and a Transformer-based encoding layer. The primary function of the patch embedding layer is to transform the input image into a sequential arrangement of flattened patches. These patches are subsequently subjected to processing by the encoder. The patches are commonly characterized by their non-overlapping nature and consistent dimensions, typically measuring 16x16 or 32x32 pixels. The encoder consists of a sequence of self-attention layers and feed-forward neural networks (FFNs). The utilization of self-attention layers in the model enables it to selectively focus on specific segments of the input sequence, hence facilitating the incorporation of extensive interdependencies among patches [25]. FFNs are employed to apply non-linear changes to the output of the self-attention layers. The Vit model incorporates various supplementary elements, like layer normalization and dropout, in order to enhance its performance and mitigate the risk of overfitting. The ViT has been developed with the objective of enhancing the processing of images in a manner that is more versatile and adaptable compared to CNNs. This is achieved by the utilization of self-attention mechanisms. When CNNs to ViT, it is seen that ViT exhibits a significantly higher computational cost. This characteristic renders ViT less advantageous for certain real-time applications. Please refer to Figure 6 for an illustration of the ViT architecture.

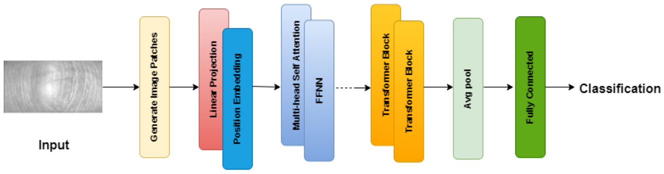

Fig. 6: Architecture of VisionTransformer model.

III. Results and Discussion

The initial dataset utilized for SCNN and AlexNet models had dimensions of 220 X 110. Subsequently, the dataset was expanded to dimensions of 224 X 224 for all other models.

During the evaluation of our scheme, we utilized assessment criteria such as accuracy, precision, recall, specificity, and F1-score. The following metrics are defined based on the values of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{5}$$

For the purpose of our image classification assignment, we applied a total of seven distinct models. Six of these models were developed based on the principles of transfer learning and were optimized using the Adam optimizer. The primary aim of this study was to develop and refine models capable of effectively classifying the owner of finger knuckle patterns, while also addressing the difficulties associated with discriminating between comparable motions made by the knuckles. All seven models were executed using the subsequent hyperparameters: a learning rate of 0.001, 8 batches, an Adam optimizer, and a stochastic gradient descent momentum of 0.9. The models DensNet, EfficientNet, GoogleNet, and ResNet-50 were trained for 2 epochs, whereas SCNN, AlexNet and Vision-Transformer were trained for a longer period of 50 epochs. The SCNN architecture consisted of three convolutional layers, filter sizes of 5x5 and 3x3, and max-pooling layers with small pool sizes of 2x2, the ReLU was used as an activation function and a softmax activation function for the output layer. The performance of the models was assessed using a five-fold cross-validation approach. Table I summarizes the metrics of performance for the models under investigation compared to other published works.

The performance evaluation findings of the seven models are presented in Table I. It is evident that, overall, SCNN, EfficientNet, AlexNet, GoogleNet, and ResNet50 respectively exhibited high levels of accuracy in their performance. The simple AlexNet and SCNN models outperformed some of complicated models may refer to their sufficiency handling such small sized datasets. The metrics of Precision, Recall, Specificity, and F1-score are included in Table I to provide further validation for comparing the models.

TABLE I: Metrics rates of performance for the applied classification models compared to previous published works.

Architecture	***Accuracy***	***Precision***	***Recall***	***Specificity***	***F1***
AlexNet	96.224	96.754	96.224	99.974	96.181
DenseNet	81.224	87.711	81.224	99.843	80.333
EfficientNet	98.176	98.485	98.176	99.987	98.137
GoogleNet	95.601	96.375	95.601	99.968	95.449
SCNN	98.3	98.62	98.3	99.991	98.251
ResNet50	92.598	94.219	92.598	99.946	92.282
ViT	79.513	80.663	79.513	99.825	79.118
VGG16 [36]	90.08	NA	NA	NA	NA
VGG19-F6 [37]	81.5	81.5	81.4	NA	81.4
ResNet34 [38]	79.02	NA	NA	NA	NA
Deep CNN [38]	96.50	NA	NA	NA	NA
FKPIndexNet [39]	97.25	NA	NA	NA	NA

Nevertheless, the performance of the vision transform model was shown to be inferior when compared to the other models. The need to resize the input data to match the fixed input size of the original model is the reason behind this phenomenon. To fulfill this criterion, the dataset underwent a resizing operation to get dimensions of 224x224x3. During the process of resizing, there is a possibility of losing essential information, which might have an impact on the overall performance. The utilization of data augmentation methods on a Vision Transformer model, like random cropping, flipping, rotating, or modifying brightness and contrast, has the ability to introduce supplementary variations to the training data, hence potentially enhancing the model's performance.

Table I shown in this study provides a comprehensive comparison between the examined models and recent works that have employed the same dataset [36]–[39] for their research. Regarding the evaluation measures for this dataset, our models exhibit encouraging performance. As a result, the experimental findings validate the efficacy of the suggested methodology in accurately categorizing and identifying FKP.

IV. Conclusion

In this paper, we used transfer learning and fine-tuning for six pre-trained deep neural networks to study their performance on FKP dataset provided by PolyU. SCNN was employed for further studying of the model complexity required to handle such types of datasets. Our experiments show that pre-trained models, such as EfficientNet, GoogleNet, and AlexNet are vulnerable to performance compared to other studied models. SCNN and AlexNet simple architecture outperformed more complex models proving their efficiency in handling small-sized datsets. In our particular scenario, we have opted to evaluate the performance of the seven models without employing data augmentation as a methodology across all models. In order to maintain a fair and impartial comparison among the seven models examined in our study, we have abstained from employing any data augmentation techniques in any of the models. This methodology enables us to evaluate the intrinsic capabilities and performance disparities across the models, solely considering their architectural design and training procedure, while disregarding any further changes in the data.

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