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Braille code classifications tool based on computer vision for visual impaired

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ABSTRACT

Blind and visually impaired people (VIP) face many challenges in writing as they usually use traditional tools such as Slate and Stylus or expensive typewriters as Perkins Brailler, often causing accessibility and affordability issues. This article introduces a novel portable, cost-effective device that helps VIP how to write by utilizing a deep-learning model to detect a Braille cell. Using deep learning instead of electrical circuits can reduce costs and enable a mobile app to act as a virtual teacher for blind users. The app could suggest sentences for the user to write and check their work, providing an independent learning platform. This feature is difficult to implement when using electronic circuits. A portable device generates Braille character cells using light-emitting diode (LED) arrays instead of Braille holes. A smartphone camera captures the image, which is then processed by a deep learning model to detect the Braille and convert it to English text. This article provides a new dataset for custom-Braille character cells. Moreover, applying a transfer learning technique on the mobile network version 2 (MobileNetv2) model offers a basis for the development of a comprehensive mobile application. The accuracy based on the model reached 97%.

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1. INTRODUCTION

According to the World Health Organization (WHO), about 2.2 billion people worldwide are blind or visually impaired [1]. Visually impaired people (VIP) and blind people face many s difficulties in learning to write and read due to a lack of teachers [2] or the high price of the learning tools. Almost all researchers introduce tools for learning reading. Kader *et al.* [3] introduces a device for pronouncing the character and making the blind sense the position of the Braille code using six solenoid actuator, or read braille text paper and pronounce it providing self-learning method for reading, also Ardiansah and Okazaki [4] provides a mobile app to translate the written Braille book into speech for learning how to read. Refreshable Braille display plays an important role in reading. The contribution of this paper is in the area of learning writing. The available writing tools are briefly described as follows: slate and stylus is the oldest Braille writing method [5] is portable but slow for note-taking, requires paper, and provides no feedback. Perkins Brallier is a mechanical device that has been widely used mechanical Braille writer, since its invention in 1951. Perkins has a key corresponding to each of the six dots of the Braille cell, a space key, and a backspace key. This device comes in a new version called smart Brallier, which was invented in 2011. It has text-to-speech audio feedback and a digital display for use by both sighted and blind individuals [6]. The price of the Perkins Brallier is high (about 1,600 $), and it is a heavy-weight device, so it is not affordable for all students. In addition, it is not a portable device.

Mountbatten Braille was invented in 1983 [7], with additional features like audio feedback and type corrections memory storage. It can connect to a computer. However, it is an expensive product (8,000 $), and, therefore, not affordable by many people and schools. Smart Braille was invented in 2011; it is an improved version of Perkins Brallier [6] because it has a text-to-speech feature. However, it is expensive. Braille note-taking devices have a refreshable Braille display and MP3 media player. BrailleNote is a portable computer [8]. Braille keyboards [9] help VIP to use smartphones or a computer; however, it needs more practice. touchscreen devices help VIP to improve their living condition. Shokat *et al.* [10] developing a machine learning English Braille pattern identification by collecting a Braille dataset from touchscreen devices.

The existing Braille writing tools face several challenges. Advanced tools are often expensive and inaccessible, while basic tools require constant teacher guidance, limiting independent learning. To address these issues, a proposed solution is to develop an affordable device for learning Braille letter placement and formation (writing techniques). This solution is divided into two parts a portable device for formatting the Braille code by using light-emitting diode (LEDs), and a deep learning model to analyze the Braille code to detect the corresponding English character. The deep learning model was trained on a dataset. The target for this stage of the research is to develop firmware and validate the idea of using deep learning to detect the written Braille code. In the future, we plan on deploying the deep learning model on a mobile app to analyze written letters and pronounce letters. It could also suggest future letters for more practice and store written content to be printed later. By empowering independent Braille learning, this solution would reduce reliance on teacher assistance and increase accessibility and affordability. This mobile app is the reason for using deep learning instead of using electrical circuit, so this technique will have more and more features. Our research contributions include:

- Designing a device Figure 1

The device forms a Braille cell using LEDs instead of mechanical devices by pressing the buttons to make a corresponding LED turn on to form the same shape as the Braille character. The design is similar to existing type writing devices as they have the same button positions. The dataset was created by using this device, to validate the idea of classifying the Braille code into corresponding English characters.

- Creating a dataset firmware

A custom dataset for the Braille alphabet is created to use it as a standard for the computer vision tasks to train the model to recognize the Braille cell and convert it to its corresponding English character.

- Develop a model based on deep learning

Recently, deep learning-based models have made great advances in many areas, for example, in object detection and natural image classification [11], [12]. Applications [13] also include speech recognition [14]. Deep learning is also currently used for Braille character recognition [15]. Moreover, it is used in applying Transfer learning techniques [16] on the MobileNetV2 model [17]. Currently, MobileNetV2 is used in many image classification research topics, such as fruit image classification [18], lung disease multiclass classification [19], waste classification [20]. Using deep learning instead of electrical circuits will lead to new improvements and extra features in the future like, self-learning mobile app, and exam provider platforms for VIP. This model has 97% accuracy and validates the idea of converting a captured image for custom Braille characters into corresponding English text based on a deep-learning approach.

Figure 1. The Designed device for simulating Braille cell

2. METHOD

This section is divided into three parts: designing the device, creating the dataset, and training the deep learning model. The designed device is similar to existing Braille keyboards. The dataset is considered as firmware for training the model. The model was developed based on MobileNetv2.

2.1. Designing the device

The process of designing the electronic device involved the following steps. Firstly, the printed circuit board (PCB) was designed using Proteus software, ensuring the proper layout of electronic components. Next, a 3D model for the box and cover was created utilizing on shape software, allowing for precise dimensions and design customization. The PCB was then printed using a computer numerical control (CNC) machine, while the box and cover were 3D printed, device is shown in Figure 1. Figure 2 shows experimental setup, where the device is put under camera phone. This device consists of buttons and 8 LEDs arranged in two columns, each containing four LEDs. Each button connects with the corresponding LED as shown in Figure 3. The arrangement of the buttons and the LEDs is similar to Perkins Brallier, where LEDs 1 to 6 represent the standard Braille six-dot cell. The stander six dots are organized into a 3×2 array, which offers 64 combinations of unique patterns. For example, in the x class shown in Figure 4, buttons 1, 3, 4, and 6 are pressed, corresponding to the Perkins Brailler keys, and the corresponding LEDs are turned on. as shown in Figure 4. We have developed a custom Braille cell with eight digits, 6 LEDs as standard, and LED 7 represents the space key, and LED 8 represents the new line key. The extra two LEDs (7, 8) enable the model to not only detect alphabetical letters but also detect spaces between words and new line action required to start a new line of text. There is another version of the Braille cell consisting of eight dots [21] arranged in a 4×2 array, which offers 256 unique combinations to represent one alphabet or a contraction of a word.

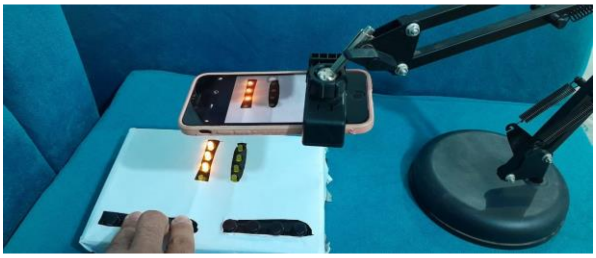

Figure 2. Experimental setup for capturing image of braille cell

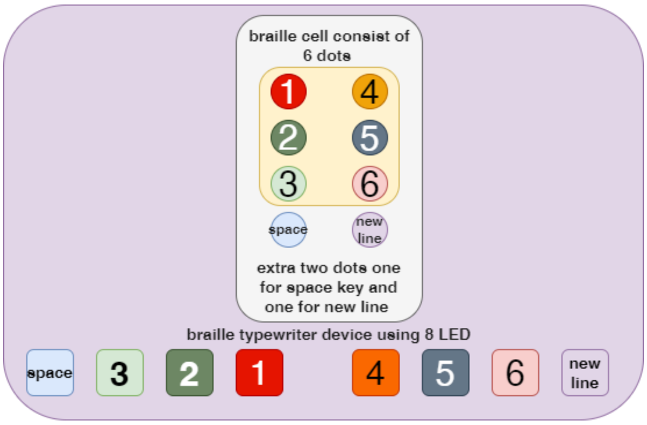

Figure 3. the device layout

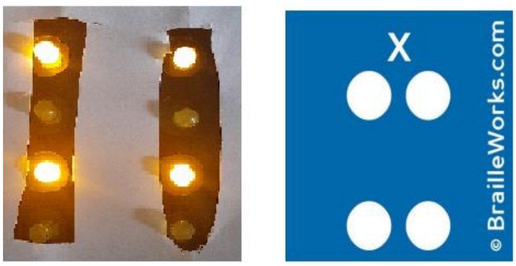

Figure 4. The generated x class with our device vs the stander x class in Braille

2.2. Creating the dataset

The dataset consists of approximately 2,200 pictures divided into 1,931 pictures for training and 259 pictures for testing. All these pictures were taken from various angles and with different brightness conditions. The dataset consisted of 37 characters in Table 1, consisting of Braille grade 1 symbols. Legge *et al.* [22] shows the difference between Braille grades. The classes contained all the alphabetical letters and punctuation, based on the Braille grade 1 standard symbols. Samples of our dataset are shown in Figure 5. To prepare the dataset for training, several steps were followed. First, multiple pictures of the same characters were captured. These pictures were then organized into 37 folders, each representing a specific Braille class. A random selection of pictures from each class was used to create the testing data, ensuring an equal number of classes. A Python script was executed to read each picture and generate a comma-separated value (CSV) file with two columns: the picture name and the corresponding class. Additionally, a one-hot encoded CSV file was created to facilitate multi-class classification. The pictures were cropped to focus only on the LEDs and were merged into a single folder. The same steps were applied to the testing data to ensure consistency.

Table 1. Training dataset classes with number of pictures with each class

Class name	Picture numbers	Class name	Picture numbers	Class name	Picture numbers
$class\_!$	57	$class\_d$	45	$Class\_m$	39
$class\_-$	56	$class\_g$	53	$class\_p$	43
$class\_a$	52	$class\_j$	42	$class\_r$	52
$class\_t$	56	$class\_'$	49	$class\_sp$	43
$class\_w$	62	$class\_0$	48	$class\_cap$	44
$class\_z$	62	$class\_c$	48	$class\_y$	95
$class\_com$	51	$class\_qs$	40	$class\_v$	56
$class\_\#$	62	$class\_e$	41	$class\_n$	53
$class\_.$	50	$class\_h$	51	$class\_q$	46
$class\_b$	53	$class\_k$	38	$class\_s$	47
$class\_u$	67	$class\_f$	52	$class\_o$	64
$class\_x$	79	$class\_i$	57		
$class\_en$	44	$class\_l$	34		

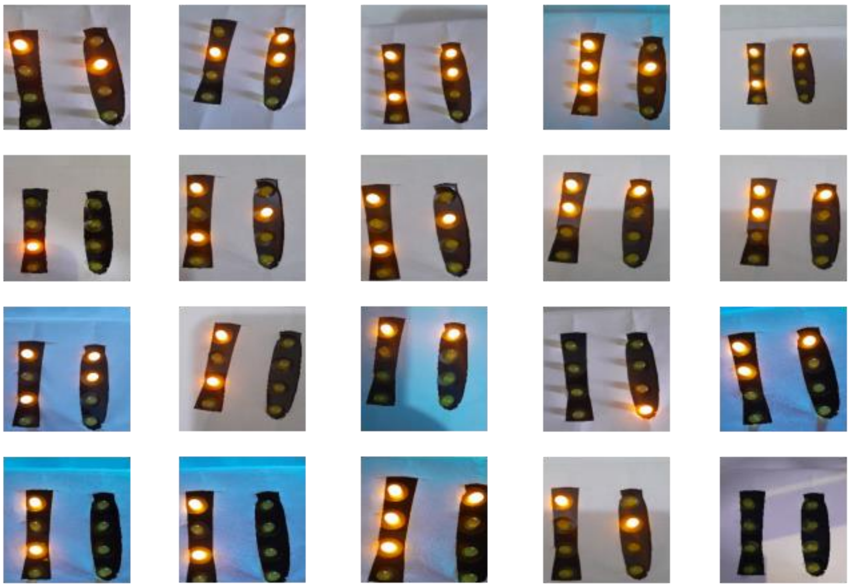

Figure 5. Custom dataset samples

2.3. Developing a deep learning model

By applying transfer learning using MobileNetv2 as feature extractors, where MobileNetv2 is a pre-trained image classification model. Transfer learning transfers the knowledge from one domain to another and also takes less time to train new models with high accuracy suitable with limited resources of central processing unit (CPU) and graphics processing unit (GPU) availability. We used MobileNetV2 architecture without any customization of the base model. MobileNetV2 architecture [16], is preferred over others due to its simple architecture and memory-efficient characteristics. The architecture contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. The proposed model consists of 3 stages, as shown in Figure 6.

First stage: labeled "block 1" is for resizing the input image to (224, 224, 3) to fit with MobileNetV2 architecture input. Second stage: labeled "MobileNetV2" is the main part of the proposed model used as a classifier, as it is more efficient and simpler in calculations. In addition, it has a convolutional neural network architecture that seeks to perform well on mobile devices from Google as it is faster than many models and uses less memory, resulting in better accuracy. Third stage: It is labeled "custom head" which consists of global average Pooling 2D, followed by a Dense layer with 37 output classes using the "Soft maximum." SoftMax activation function. The SoftMax activation function is commonly used for multiclass classification in deep learning. It is used to compute probability distribution from a vector of real numbers. The SoftMax function [23] produces an output between 0 and with the sum of the probabilities being equal to 1. The SoftMax formula [24] appears in (1).

$$f(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)} \tag{1}$$

Model training is carried out in three steps. Image preprocessing using the Keras image data generator class [25]. This class offers various techniques for image preprocessing which is utilized to rescale both training and test images to a range of 1/255. After preprocessing, the data needs to be formatted as a three-dimensional matrix such as 224×224×3 in a way that the neural network can understand.

Feature extraction by applying transfer learning on MobileNetV2 architecture which was pre-trained on a large dataset like ImageNet [26], where the base layers are frozen, and only the custom hidden layers are trained with root mean squared propagation (RMSprop) optimizers [27] using a learning rate of 0.001. Additionally, the dataset is split, allocating 20% of the training data for the validation process. The classification step involves employing the SoftMax activation function. It allows for the detection of the correct class of the input image. Table 2 displays the settings that were used.

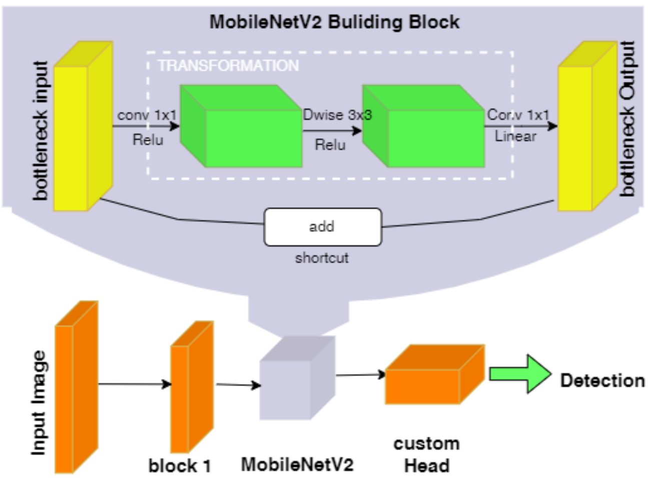

Figure 6. MobileNetV2 building block

Table 2. Settings for the training process

Learning rate	Epochs	Batch size	Optimizer	Loss function
0.001	100	30	RMSprop	categorical cross entropy

3. RESULTS AND ANALYSIS

The accuracy of detecting the English character corresponding to Braille code. reaches almost 97% as shown in Figure 7. The validation loss of the proposed model reaches a very low value of 0.19 as shown in Figure 8. The performance and evaluation of the model are measured using a confusion matrix [28]. The confusion matrix of the proposed model is shown in Figure 9. The evaluation of the model is based on several factors, which are: accuracy, precision, sensitivity, and F1-Score. The calculations and measurements are given by (2) to (6) [29].

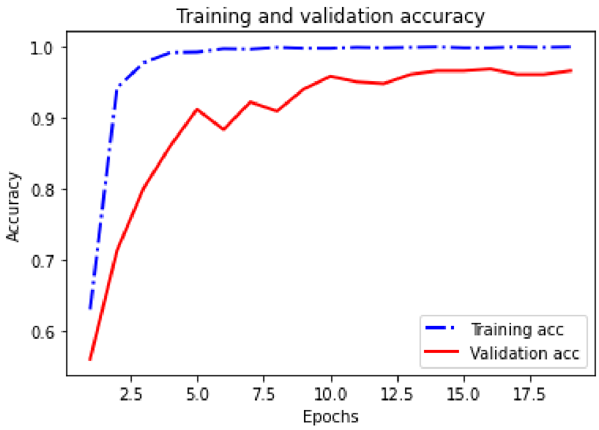

Figure 7. Training and validation accuracy graph

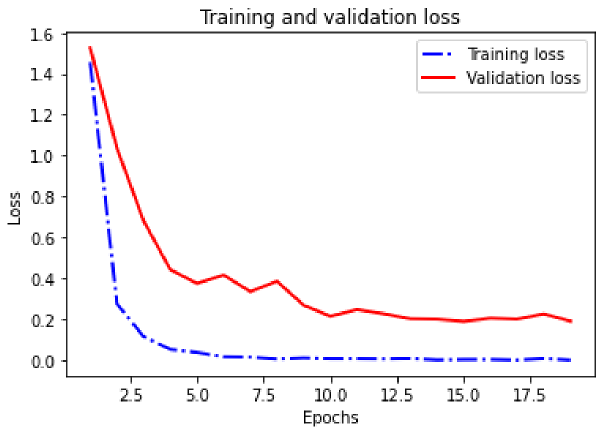

Figure 8. Training and validation loss graph

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

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

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

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

$$Sensitivity = Recall = \frac{TP}{TP+FN} \tag{6}$$

where *TP*: true positive, correct prediction. *TN*: true negative, correct prediction. *FP*: false positive, false or bad prediction. *FN*: false negative, the worst prediction result.

Figure 10 shows the predicted labels vs true labels for the final model output result after training. Table 3 shows a comparison between existing solutions for Braille devices and methods. You can notice that our proposed device is technology-based, portable, and cheaper with reasonable accuracy compared to other existing solutions. This high accuracy of the model is a validation of using computer vision in Braille learning writing techniques without using any expensive tools or heavy and nonportable typewriter. With the help of this model, many products will be developed based on it. This method is considered a new direction of learning Braille writing compared with traditional tools which use electrical circuits. One of the future products is a mobile app based on the proposed model. This app will serve as a self-learning platform, acting as a virtual teacher to detect and pronounce Braille code. Additionally, it can suggest words to be written and provide corrections. Another feature can be the ability to prepare, administer, and correct exam papers, helping schools significantly. Each student can install the application on their own device, offering schools a much cheaper solution. Moreover, this app can be used as a note taking, storing written words to be printed using Brailler printers.

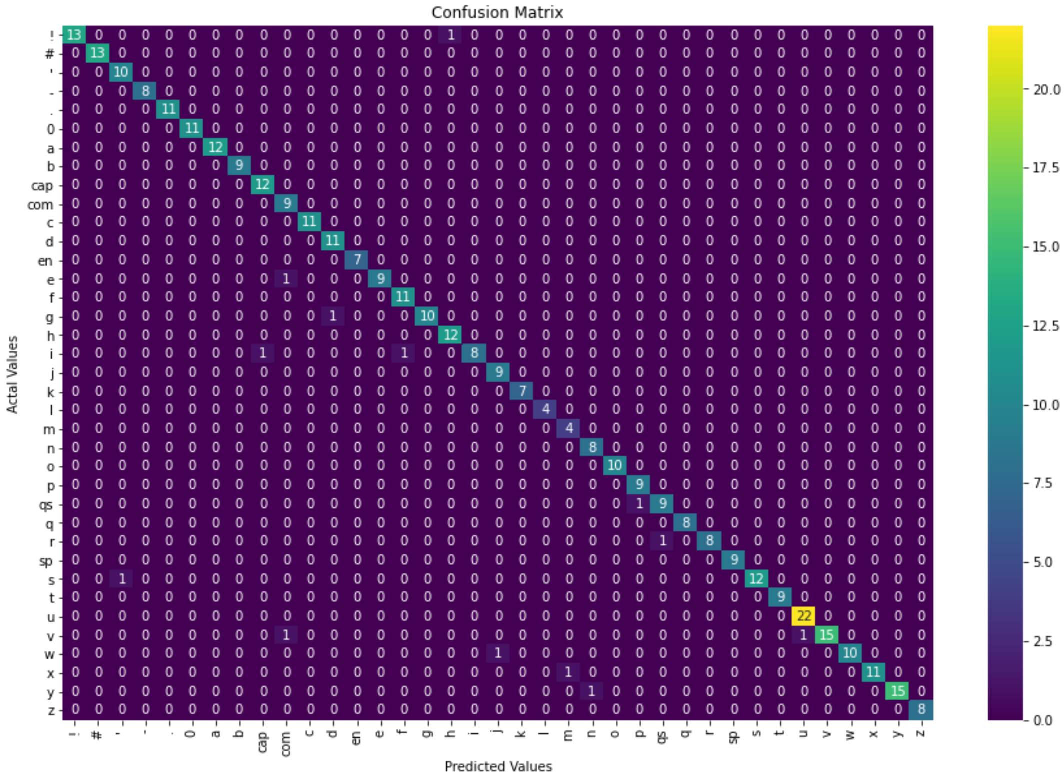

Figure 9. Confusion matrix of the proposed model

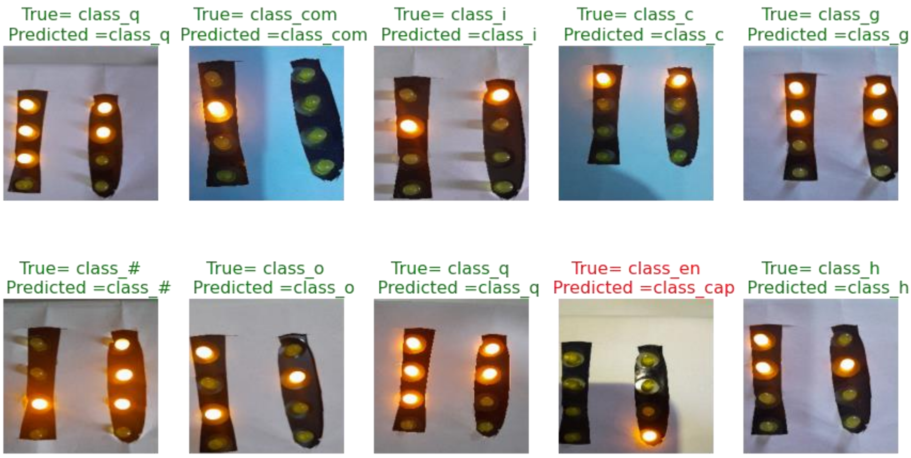

Figure 10. Predicted labels vs true label

Table 3. Comparison between existing solutions for Braille

Device name	Price	Problem with the technics	Portable	Technology-based	Accuracy
Perkins	1600 $	Old mechanical design and heavy	No	No	100 %
Slate and Stylus	80 $	Very slow and too old and without any feedback	Yes	No	100 %
Smart Brallier	8000 $	Very expensive, maintenance not always available	No	Yes	100 %
Our method	10 $	----------------	Yes	Yes	97 %

4. CONCLUSION

This paper introduces an innovative solution for blind and visually impaired individuals, serving as a writing aid tool. By using a simple designed portable device, a custom dataset was created consisting of approximately 2,200 pictures of custom Braille characters divided into training and testing sets. By employing transfer learning techniques with MobileNetV2, a deep learning model was developed and tested. The training process was expedited and simplified. The model was then evaluated on the testing dataset, demonstrating its ability to accurately predict English Characters corresponding to Braille characters with a 97% accuracy rate. The device with the model is an innovative direction for producing typewriter tools based on computer vision instead of expensive electrical tools, leading to the development of cheaper tools for blind people. For example, this model provides the foundation for the development of a comprehensive mobile app helps in self-learning braille writing techniques.

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