IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 6, December 2025, pp. 4652~4660
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i6.pp4652-4660

Deep learning approaches for Braille detection and classification: comparative analysis

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Article Info

Article history:

Received May 18, 2024
Revised Sep 8, 2025
Accepted Oct 18, 2025

Keywords:

Braille classification
Braille detection
Convolutional neural network
DenseNet
MobileNetV2
ResNet
ResNeXt

ABSTRACT

This study proposes a hybrid approach to Braille translation leveraging the strengths of both YOLO for object detection and multitude of classification models such as ResNet, and ResNet for accurate Braille character classification from images. Upon comparing numerous models on various performance metrics, ResNet and DenseNet outperformed other models, exhibiting high accuracy (0.9487 and 0.9647 respectively) and F1-scores (0.9481 and 0.9666) due to their deep, densely connected architectures adept at capturing intricate Braille patterns. CNNs with pooling showed balanced results, while MobileNetV2's lightweight design limited complex classification. ResNeXt's multi-path learning achieved respectable performance but lagged behind ResNet and DenseNet. In the future the results from our study could be further explored on contracted Braille recognition, be adapted to various Braille codes, and optimized for mobile devices, for real-time Braille detection and translation on smartphones.

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1. INTRODUCTION

Visual impairment affects a significant portion of the global population, with India alone having approximately 70 million visually impaired individuals, including 4.95 million blind people and 0.24 million children. For these people, Braille remains the primary medium for literacy and communication. A study conducted in Delhi NCR has shown that visually impaired individuals face significant medication management challenges due to lack of extensive use of Braille in daily life, which can lead to severe health consequences [1]. However, the integration of advanced technologies has the potential to significantly enhance inclusion and connectivity in our increasingly digital world. Recent advancements include braille displays with servo motors utilizing Google's Tesseract OCR engine [2], IoT devices designed for recognizing specific Braille characters [3]–[8], and the BrailleNet model, which incorporates foreground attention and semantic learning [9]. Building on these developments, convolutional neural networks (CNNs) offer significant potential for Braille detection and classification, enabling broader recognition of diverse Braille characters and enhancing accessibility for visually impaired individuals [10]–[15]. Nasir *et al.* [16] proposed an Android application that utilizes a CNN-based visual recognition model with the TensorFlow object API and single shot detector (SSD) using a pre-trained MobileNetV2. This application assists visually impaired users in their daily activities without the need for an internet connection, highlighting the practical potential of CNNs in real-life tasks.

While some studies have compared the performance of various CNN models for Braille recognition and classification [17], [18], a comprehensive analysis of advanced deep learning architectures such as ResNet, DenseNet, and ResNeXt is still lacking [19]–[23]. This gap in research limits our understanding of the full potential of these architectures for Braille recognition tasks. Additionally, the computational efficiency crucial for real-time Braille recognition on mobile devices is often overlooked. This oversight limits the practical applicability of many proposed solutions, especially for everyday use by visually impaired individuals. Furthermore, most research focuses on specific languages, with a notable lack of solutions for diverse language requirements [24], [25]. To address these challenges, we propose a hybrid approach that leverages the strengths of both the YOLO model for rapid Braille character detection and specialized CNNs for detailed classification. This separation of detection and classification processes aims to balance speed and accuracy, providing a scalable, modular solution adaptable to various use cases and potentially improving overall efficiency in Braille recognition.

In this paper, we present a thorough comparison of various CNN models' performance in Braille character classification. The models compared include architectures like ResNet, DenseNet, MobileNetV2, and ResNeXt. With this study, we aim to contribute to the development of more efficient, versatile, and practically applicable Braille detection and classification systems, ultimately enhancing the quality of life for visually impaired individuals worldwide.

2. METHOD

2.1. Braille character detection using YOLOv8

To achieve a translated Braille, the first task would be to detect the Braille characters present in the input image. This is achieved by taking advantage of the YOLOv8 object detection model trained on a Braille dataset [26]. This dataset consisted of 2000 annotated images of braille characters in various scenes. The detected characters were cropped and given as input to the classification model which then translated them. The use of two separate CNN models for the tasks of detection and classification ensures accuracy by leveraging the strengths of each model. The general process of detecting Braille characters using YOLOv8 is depicted in Figure 1.

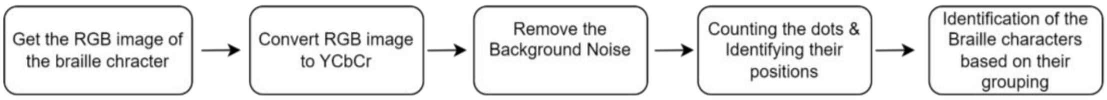

Figure 1. General working of Braille character detection model

Initially, RGB image that contains Braille characters is converted from the RGB color space to the YCbCr color space, a widely used color encoding system in digital image and video processing. This allows for better handling of luminance and chrominance which enhances the contrast between Braille dots and their background allowing for optimal detection and classification. After conversion preprocessing is applied on the image to remove background clutter and improve performance by eliminating noise and subsequently false positives. YOLOv8 model divides the input image into a grid and makes predictions within each grid cell regarding the location of bounding boxes and class probabilities for the objects it detects. The model calculates confidence scores to determine the likelihood that a particular bounding box contains a Braille character. To increase detection accuracy in the context of Braille, the pre-processed image serves as the input to YOLOv8, which detects individual raised dots that form Braille characters. These arrangements of dots within a 2×3 grid are identified based on their size, shape, and spatial arrangement.

2.2. Braille character classification

After detection, the YOLOv8 model returns bounding box coordinates for each of the Braille characters which are processed further to extract the characters. This is performed with the aid of the OpenCV, which takes the bounding box coordinates returned by YOLOv8 and crops the relevant region from the original image, isolating every Braille character. These cropped characters can now be sent as an input to several deep learning-based models to classify them accurately. In this study, we aim to evaluate and compare the performance of various deep learning model architectures in classifying Braille characters. For Braille character classification, the dataset [27] used constituted numerous images of each Braille character in a 28×28 BW scale. The data also went through several types of data augmentation including width height shift, rotation, etc. First, we considered CNNs with pooling, with three convolutional layers with 32, 64, and 128 filters respectively. This CNN based Braille classifier applies a simple architecture that is followed by max pooling to reduce spatial dimensions. The convolutional layers efficiently capture the fine spatial detail and hierarchical features in the input image with a kernel size of 3×3. The model also includes fully connected layers to perform classification with hidden layer size of 512. The dropout layer is then incorporated in the fully connected section and aims to reduce the overfitting and enhance the model's performance.

This is followed by residual neural networks (ResNet) that features residual blocks which integrates skip connections to facilitate gradient flow and reduce the problem of vanishing gradient. Initially, the network begins with a convolution and max pooling layer, it is then followed by pre-residual blocks that progressively decrease spatial dimensions and deepen feature extraction. Each residual block contains two convolutional layers supported by batch normalization (BatchNorm) and rectified linear unit (ReLU) activation to stabilize training while also enhancing feature learning. Another model that we examined was, densely connected convolutional networks (DenseNet). The classifier takes the advantage of a dense connectivity pattern where each layer is connected to every previous layer ensuring efficient learning as well as promotes feature reuse. The architecture starts with an initial convolutional layer followed by dense blocks where the inputs are concatenated with the outputs of the previous layers. The number of feature maps and downsample spatial dimensions are reduced by introducing transition layers between the dense blocks.

We have also tried other models such as MobileNetV2 and ResNeXt. MobileNetV2 is designed for efficient inference on mobile and embedded devices with limited computational resources. It achieves efficiency through depth-wise separable convolutions which significantly reduces the computational cost while maintaining representational capacity. MobileNetV2 's lightweight architecture making it suitable for real-time inference on devices having constrained resources, especially in scenarios where computational efficiency is of utmost importance. Lastly, the ResNeXt model, which is an advanced variant of ResNet model that aims to enhance feature diversity by employing the concept of cardinality by using grouped convolutions. The model begins, with an initial convolution and BatchNorm layer, it is then succeeded by four ResNet blocks that downsample spatial dimensions and increases the feature depth. Lastly, the model concludes with the global average pooling and a fully connected layer for classification utilizing cardinality to enhance representational power and efficiency without significant increase in parameter count.

3. RESULTS AND DISCUSSION

For model evaluation, standard metrics like accuracy, precision, recall, and F1-score were calculated for each model variant. Each model was trained for 10 epochs. Confusion matrices from different model variants were also compared to identify common misclassifications and areas of disagreement among the models.

3.1. Convolutional neural networks with pooling

From Figure 2 we can infer that the loss curve demonstrates a steady decline and eventual convergence. The accuracy curve shows a rapid initial increase, indicating strong learning progress. From the confusion matrix as shown in Figure 3, we can identify a few instances of misclassification, however, these are negligible and do not significantly impact the real-world application.

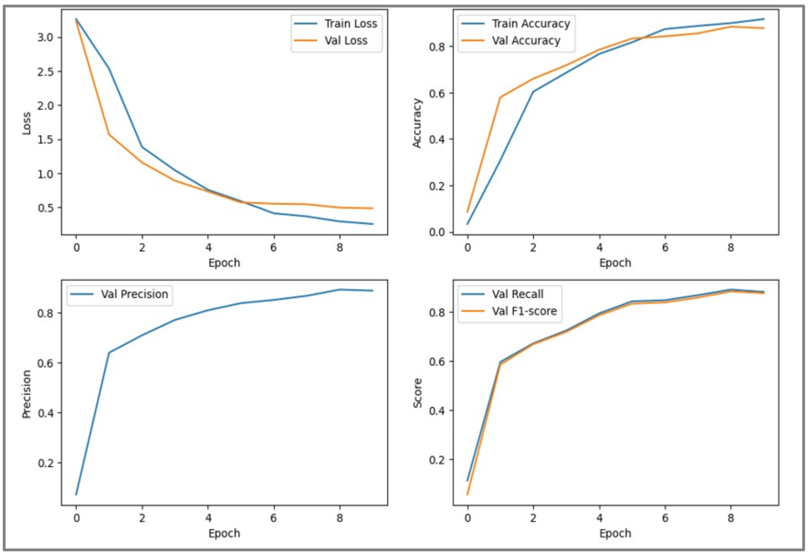

Figure 2. Graphs containing loss, accuracy, precision, and F1 score of CNN with pooling model

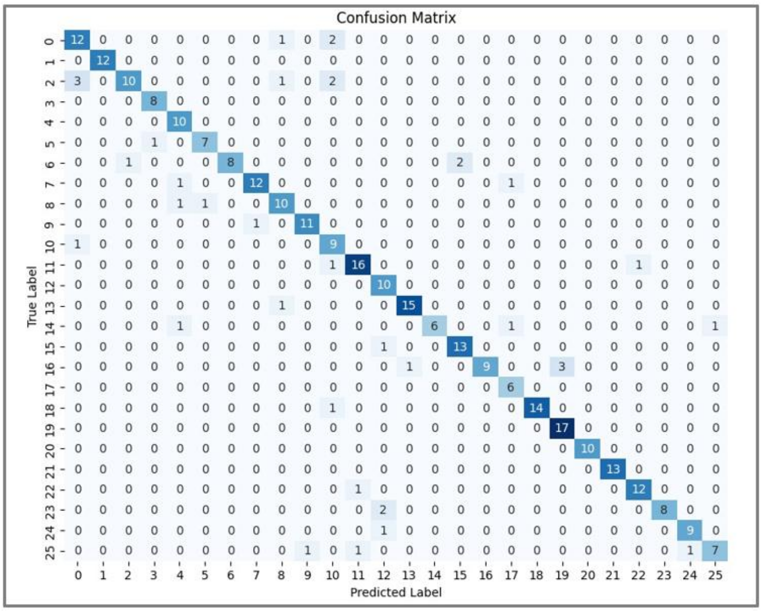

Figure 3. Confusion matrix for CNN with pooling model

3.2. ResNet

The performance results of ResNet are evaluated and shown in the Figures 4 and 5. It is evident from the figures that there is a spike in validation loss and drop in accuracy around epoch 5, suggesting instability but, despite this, the model recovers in due time boasting the ability to overcome brief setbacks. The final epochs show a slight gap between training and validation accuracy, but it is not significant enough to suggest overfitting. Figure 6 demonstrates the actual detection and classification performed by the hybrid Yolov8 and ResNet model on images having Braille text.

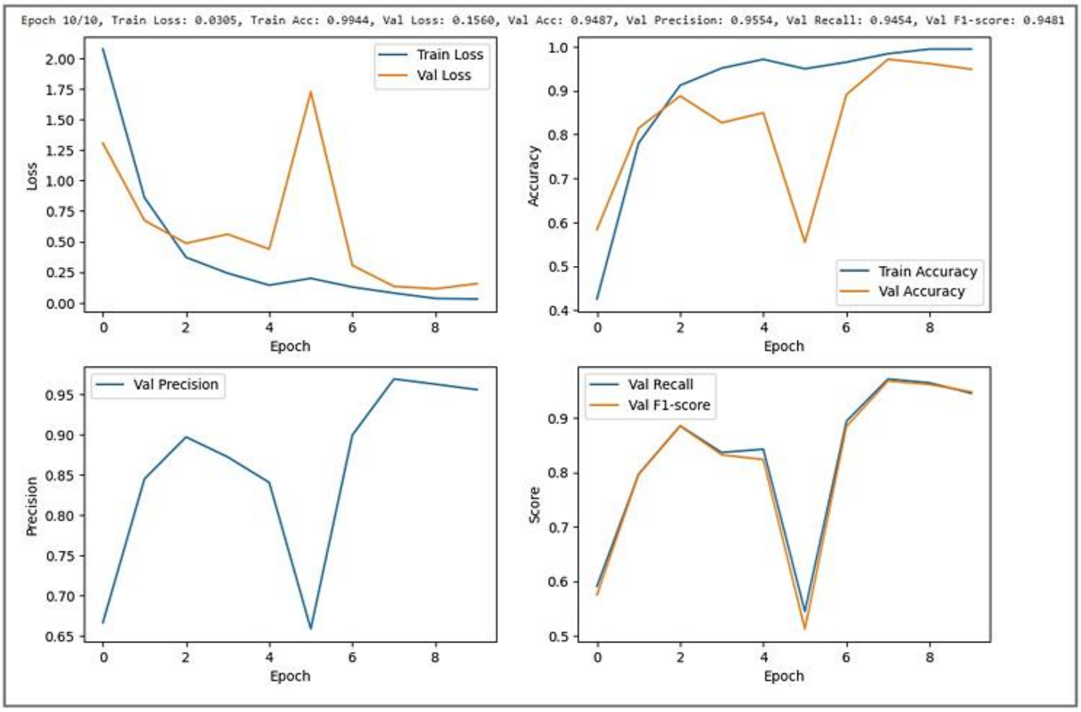

Figure 4. Graphs containing loss, accuracy, precision, and F1 score of ResNet model

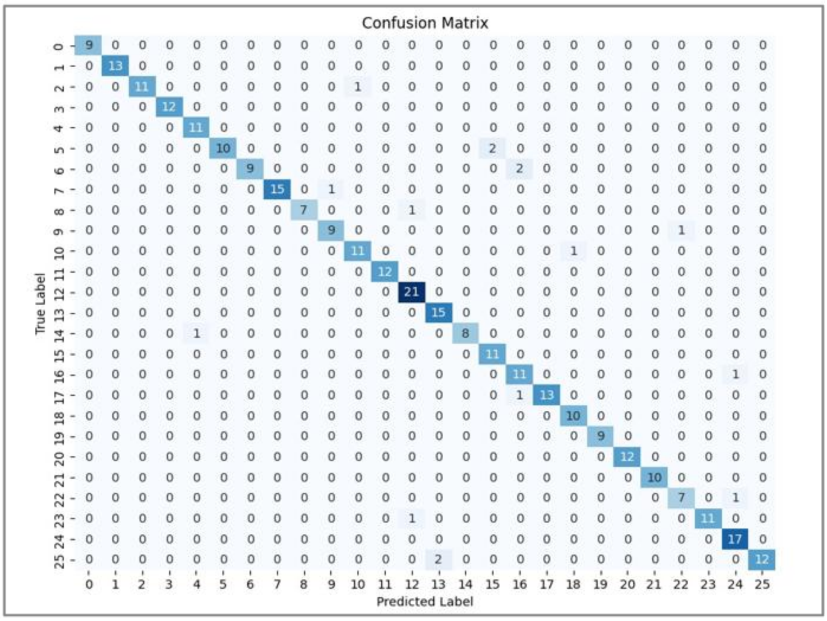

Figure 5. Confusion matrix for ResNet

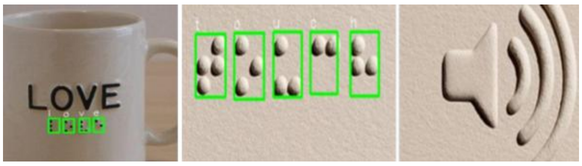

Figure 6. Working of Braille language classification model for images using ResNet

3.3. DenseNet

The performance result of DenseNet model is evaluated and shown in the Figure 7. We can infer that the training process shows significant instability, with large fluctuations in validation loss and accuracy but, this is eventually converged to a high-performance state. There is a noticeable gap between training and validation accuracy in the later epochs, suggesting overfitting but, it is not severely impacting generalization.

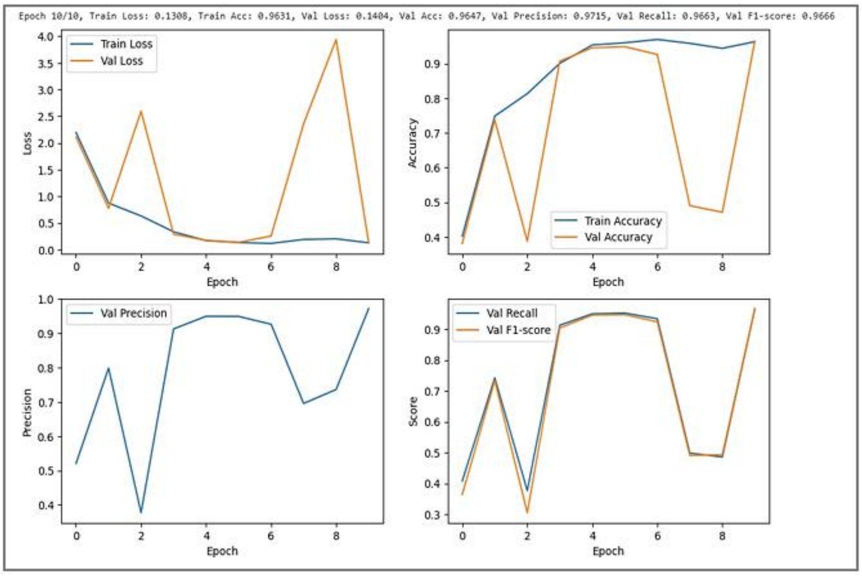

Figure 7. Graphs containing loss, accuracy, precision, and F1 score of DenseNet model

3.4. MobileNetV2

The MobileNetV2 model demonstrated reasonable learning progress, with decreasing loss despite low accuracy, as shown in Figure 8. However, a significant number of misclassifications are evident in the confusion matrix. This critically impacts the model's real-world applicability.

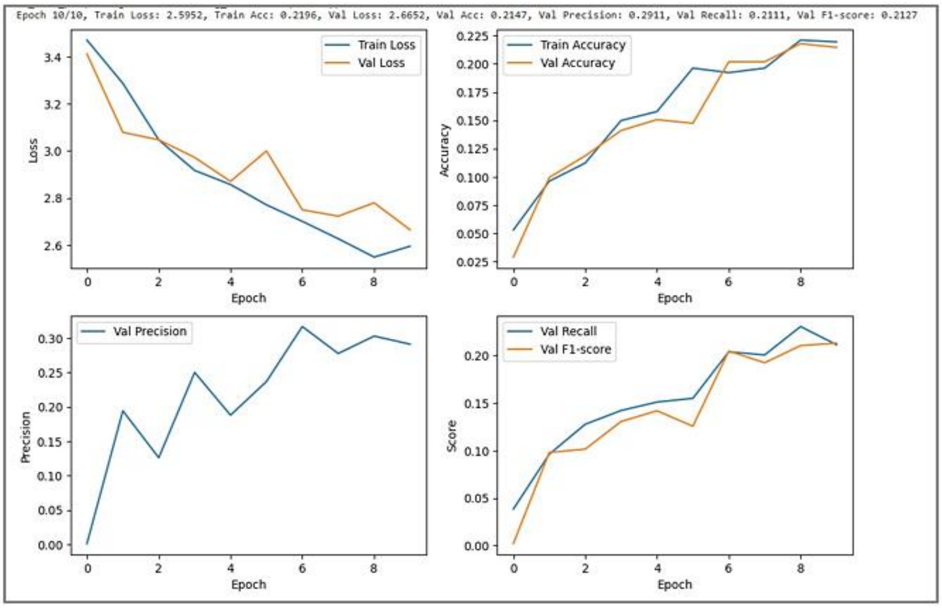

Figure 8. Graphs containing loss, accuracy, precision & F1 score of MobileNetV2 model

3.5. ResNeXt

The performance result of DenseNet model is evaluated and shown in the Figure 9. As we can see, the training process shows a smooth learning curve with both training and validation loss decreasing steadily. Also, unlike the DenseNet model, this model shows stable learning without dramatic fluctuations in performance. Overall, it shows more consistent performance across epochs compared to DenseNet, but with lower overall accuracy.

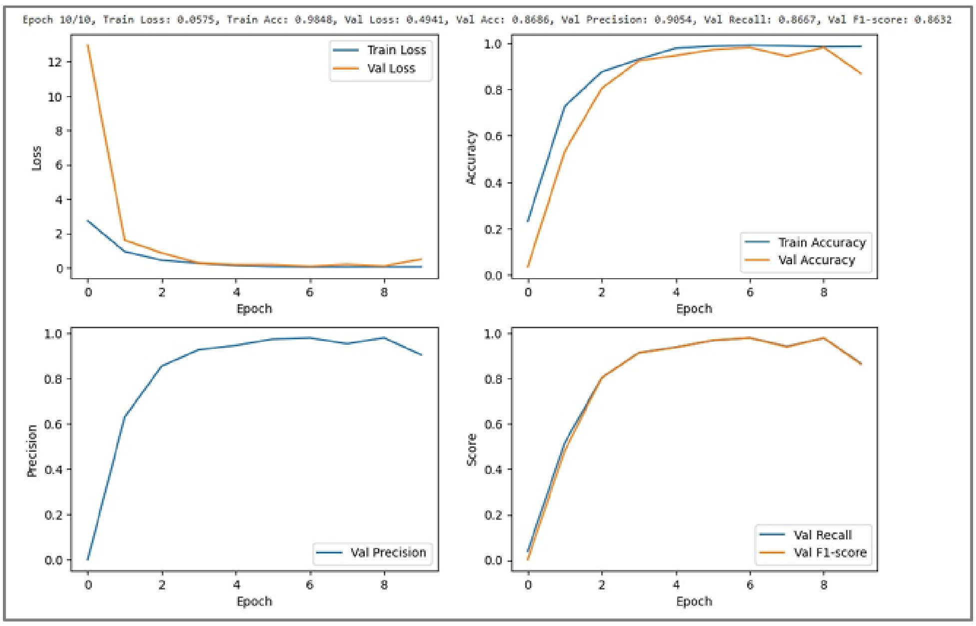

Figure 9. Graphs containing loss, accuracy, precision, F1 score of ResNeXt model

3.6. Discussion

We have compared the performance of all the models under consideration in Table 1. Based on that we have inferred that ResNet and DenseNet demonstrated superior performance, with high accuracy, precision, recall, and F1-scores, indicating effective learning and generalization capabilities. One of the major limitations that were faced during our research was the lack of high-quality dataset leading to sub-optimal detection for real world images. In a practical application this limitation will need to be addressed by creating a new extensive dataset that would work better in real world conditions. Despite this CNN with pooling showed balanced performance and will benefit from further training. MobileNetV2 exhibited significantly lower accuracy and precision, suggesting limitations in its lightweight architecture for complex image classification tasks. In comparison to Adru *et al.* [17], which explored models like ResNet50, Xception, and SqueezeNet, our work focuses on CNN with pooling, ResNet, DenseNet, and MobileNetV2. While the reference paper observed a high accuracy of 94.55% using a custom CNN, our ResNet and DenseNet models showed better accuracy and generalization, with fewer instances of instability across epochs thereby showing high potential for Braille character recognition in real-world applications. ResNeXt achieved respectable performance, but slightly lower compared to ResNet and DenseNet, indicating potential for improvement with additional training or architectural modifications.

Table 1. Comparison of models used for Braille classification

Model	Accuracy	Precision	Recall	F1-score
CNN with pooling	0.8782	0.8803	0.8773	0.872
ResNet	0.9487	0.9554	0.9454	0.948
DenseNet	0.9647	0.9715	0.9663	0.966
MobileNetV2	0.2147	0.2911	0.2111	0.212
ResNeXt	0.8686	0.9054	0.8667	0.863

4. CONCLUSION

Our study thoroughly examined and evaluated the performance of several deep learning architectures including CNNs with pooling, ResNet, DenseNet, MobileNetV2, and ResNeXt. We leveraged the YOLOv8 object detection model for efficient Braille character detection from images which is then followed by the application of different deep learning model for the classification of characters. The comparative analysis of the deep learning models has brought us to the conclusion that the ResNet and DenseNet models have outperformed other models by demonstration higher accuracy, precision, recall and F1-scores. These architectures involve densely connected layers which enables effective learning and generalization capabilities. Such features are essential for capturing the intricacies and spatial arrangement of Braille characters. On the other hand, the CNN with pooling model has a mediocre performance indicting its potential for Braille classification task however, the MobileNetV2 's light-weight architecture and design for efficiency did not perform up to the mark. ResNeXt architecture performed well but slightly less than ResNet and DenseNet, it however still holds promise for future architectural optimizations or ensemble techniques that could potentially enhance its performance. Our current research is solely focused on translation of individual Braille cell into an English letter, letter by letter. Future work could explore the recognition and translation of contracted Braille, where entire words or common letter combinations are represented by single Braille cells. Each country has its own Braille code, our research considers Unified English Braille (EBU) code, future work could involve working on other Braille codes. Furthermore, the best-performing models (ResNet and DenseNet) could be optimized for mobile devices, enabling real-time Braille detection and translation on smartphones.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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