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Original Article

An Ensemble Transfer Learning Model for the Automatic Handwriting Recognition of Kurdish Letters

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Abstract

Automatic handwriting recognition is a fundamental component of various applications in various fields. During the last three decades, it has become a challenging issue that has attracted much attention. Latin language handwriting recognition has been the primary focus of researchers. As for the Kurdish language, only a few researches have been conducted. This study uses a Kurdish character dataset, which contains 40,940 characters written by 390 native writers. We present an ensemble transfer learning-based model for automatically recognizing handwritten Kurdish letters using Densenet-201, InceptionV3, Xception, and an ensemble of these pre-trained models. The model's performance and results obtained by the proposed ensemble model are promising, with a 97% accuracy rate, outperforming other studies on Kurdish character recognition.

Keywords

Transfer Learning, Handwriting Recognition, Machine Learning, Ensemble Learning.

I. Introduction

The ability to automatically recognize human handwriting from different sources such as on paper, touch-screen, or any device that the user can write its handwriting is known as handwriting recognition. Any Scan-entered handwriting is regarded offline, but pen-entered handwriting is considered online [1]. Since there are typically differences in the handwriting of different individuals, handwriting recognition in computer vision is considered a challenging problem. Additionally, a single author's handwriting may vary somewhat from time to time [2].

Distortions and pattern diversity are the main causes of the primary challenges in handwriting identification, and this leads to the need and crucial necessity of feature extraction. An automatic selection of features is needed since a manual process may lead to the need for more information available for the right prediction of the class character. Nonetheless, because of increased dimensionality, a high number of features typically causes issues. Many methods have been used for Handwriting recognition, such as traditional machine learning algorithms and, recently, convolutional neural networks (CNNs) [3, 4].

One of the two major Kurdish dialects is Central Kurdish (Sorani). Approximately 9 to 10 million people speak the Sorani dialect, and the majority of the speakers reside in both Iran and Iraq [5, 6]. The number of characters of this dialect is 35-character consisting of the Arabic/Persian alphabet with modifications. Also, it contains some newly replaces characters which were replaced in recent years, such as (ك), which has been replaced by (ک) in the Kurdish language [7].

The Kurdish language has one of the most complicated writing forms, derived from the traditional Eastern pattern of line drawings for characters. The form of a character is very composite and resembles that of a number of other characters. Nonetheless, each character has unique characteristics. Despite the fact that Kurdish language characters can be composite and have a high degree of similarity, these characteristics might be generalized as the individual's handwriting [8, 9].

This paper proposes a weighted average ensemble transfer learning approach to recognize Kurdish handwritten characters. The first three pre-trained transfer learning models are used, which are InceptionV3, DenseNet201, and Xception mode. Each model is trained on the dataset separately, and finally, a weighted average ensemble of these three models is derived, resulting in a higher performance compared to each model individually.

A. Main Contributions

1. Effective Utilization of an Existing Kurdish Character Dataset: Leveraged a comprehensive dataset comprising 40,940 characters from 390 native writers, demonstrating the model's capabilities in a real-world context.

2. Development of an Ensemble Transfer Learning-Based Model: Innovatively combined Densenet-201, InceptionV3, and Xception models, showcasing a unique approach in the field of character recognition.

3. Achievement of High Accuracy in Kurdish Character Recognition: Attained a 97% accuracy rate, significantly outperforming previous studies in Kurdish character recognition, marking a substantial advancement in this niche area.

4. Contribution to Linguistic Inclusivity in Technology: By advancing Kurdish character recognition, the research contributes towards bridging the gap in technology for less-represented languages.

The rest of the paper is directed as follows: Section 2 contains a literature review, where we have discussed various previous studies related to Kurdish character recognition. Section 3 consists of the methodology used in this study, where each model which has been used is presented. In Section 4, details of the experiments carried out on the proposed model are described, while the results and discussion are presented in Section 5, and finally, the conclusion of the study is written in Section 6.

II. Literature Review

Kurdish handwritten recognition is a challenging yet crucial field of research, aiming to develop robust systems that can automatically recognize and interpret handwritten text in the Kurdish language. Kurdish, as an under-resourced language, presents unique challenges in the realm of handwritten recognition due to its diverse script variations and limited availability of labeled data. This literature review overviews key developments and trends in Kurdish handwritten recognition.

Character recognition research for the Kurdish language has been conducted extremely infrequently, and the published research focuses either on offline or online character recognition. The systems of Kurdish writing are among the most intricate and profound. The character has a relatively generic form that is similar to other characters. However, each character continues to be unique. These traits could be categorized as handwriting in general. Bayan Omar Mohammed's research can be considered one of the earliest studies made on the recognition of Kurdish characters [9]. Her research aims to concentrate on the characters of the Kurdish language to extract geometric moment features for the shape characters. Additionally, thorough inspection and investigation will validate the existence of individual traits; this is why Invariant Discretization was proposed. Invariant Discretization benefits improve when the level of recognition for each handwriting is raised, even though the solitary of handwritten Kurdish letters is the main focus.

To understand solitary Kurdish handwritten letters, fuzzy logic classifiers are being researched as well. Neural networks were one of the many techniques used for character recognition and were utilized by Zebardast et al. [10]. This is a good method for understating Kurdish alphabet recognition since, according to the learning capacity and process flexibility for certain applications used in the areas of pattern recognition, neural networks have shown great success. The Latin and Arabic alphabets are available in two manuscripts for the Kurdish language. Their research focused on identifying the Kurdish language (Latin scripts) using artificial neural networks, namely the Multilayer Perceptron (MLP) and a backpropagation learning algorithm. Performance is 81.2677 percent during the evaluation stage and 85.1535 percent throughout the training stage. The approach proposed in this paper can be used for all languages using the Latin alphabet.

Zarro and Anwer developed a hybrid model for character recognition, which combined both the Harmony Search algorithm and the Hidden Markov Model [11]. In line with the majority of past publications, in this study and as an additional classifier, the Markov model was employed instead of the primary classification strategies. Characters are divided into more manageable groups according to structural components using the HMM model and a common directional matrix. Through this method, the latter recognition stage's computation time was reduced. Systematic and representative movement patterns are used by the Harmony search method as a fitness function. In addition, the real function is used to reduce the matching rate through fitness function measurements. A dataset containing 4500 words and 21,234 typescripts in various locations was used to assess this method. The system's successful recognition rate was 93.52 percent.

Another technique that has been used for the recognition of Kurdish text is Tesseract LSTM, a well-liked optical character recognition (OCR) engine trained to recognize a variety of common languages, which has been the subject of research [12]. However, if the training data and resources are not accessible, the output will be less accurate. Utilizing a training dataset for a language with a comparable script proposes a solution to the issue of sparse data in training Tesseract LSTM for a new language. The experiment's target language is Kurdish, so accuracy rates have reached 95.45%.

Additionally, Ahmed et al. [13] attempted to develop and design a Kurdish handwritten character recognition model by utilizing deep learning techniques, in which a Deep Convolutional Neural Network model was employed. A Kurdish dataset containing 40 thousand of the Sorani dialect character images was fed to the model to train and test. The experimental results in the proposed model showed a 96% accuracy in the test phase.

A summarization is presented of the most related research to our work along with their accuracies in Table I.

III. Methodology

The proposed approach for Kurdish handwritten character recognition consists of utilizing three pre-trained transfer learning models, namely inceptionV3, DenseNet201, and Xception.

A. InceptionV3

Transfer learning, which works on the reuse of a trained previous model and applying its obtained knowledge to a new model, has grown to be one of the main strategies used in Inception V3 for image classification. It employs a minimal amount of data to speed up training and improve performance. One of the transfer learning models is InceptionV3, which its foundation is Convolutional neural networks aimed at image classification. The InceptionV3 model came about as an improved version of the original InceptionV1 model, which was released in 2014 under the name Google Net. Developed by the Google team, as the name suggests. A 48-layer convolutional neural network called Inception-v3 uses convolutional architecture. A trained version of this network can be obtained as it is already trained on the ImageNet database, which contains a wide range of image classes and millions of images. Gives the model the ability to categorize images into a thousand classes of images ranging from objects to animals and all kinds of image classes. This led the model to obtain knowledge and details of feature representations and patterns on a variety of different images. InceptionV3 input size by default is 299 pixels. An inception model that concatenates several inceptions was proposed in InceptionV3 to create a new filter by combining convolutional filters of various sizes. The computational complexity is decreased by reducing the number of parameters that must be taught [14]. InceptionV3 architecture is presented in Fig 1.

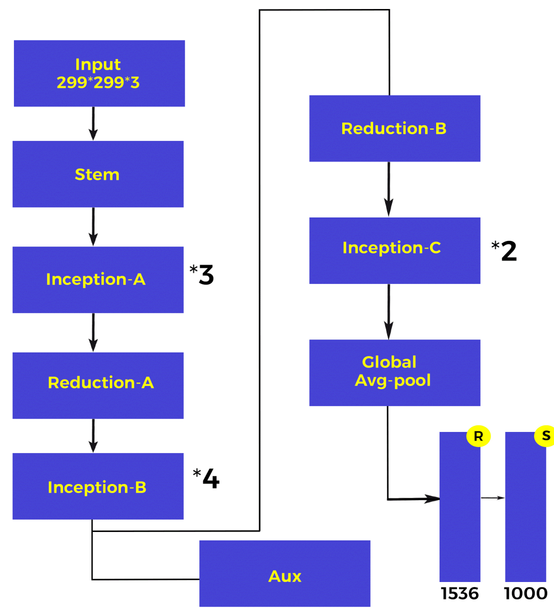

Fig. 1. InceptionV3 Architecture.

B. DenseNet201

DenseNet201 is another powerful transfer learning pre-trained model which consists of 201 layers. This model is also being trained on the ImageNet dataset, which consists of millions of photos ranging between a thousand classes of images. To address the declining accuracy brought on by high-level neural networks' disappearing gradient, DenseNet was created. Simply said, the information disappears before getting to its destination because of the longer journey between the input layer and the output layer [15].

There are four DenseBlocks in each design, each with a different number of layers. In the previous version of the DenseNet model, such as DenseNet-121, four dense block layers exist in the model, which is [6,12,24,16], whereas in DenseNet-169, the four dense block layers are [6,12,32,32]. Each layer in the DenseNet architecture is linked to all the other layers, which paved the way for the rise of the name Densely Connected Convolutional Network. In this architecture, for L layers, there is an L(L+1)/2 direct connection, and for each layer, all of the precedented layer's feature maps are

TABLE I. DIFFERENT TECHNIQUES COMPARISON ON KURDISH CHARACTER RECOGNITION

Study	Methodology	Dataset	Accuracy Performance
[10]	MLP Artificial Neural Networks	Latin-Kurdish letters Dataset	81.2677%
[11]	Harmony Search Algorithm and Hidden Markov Model	Kurdish alphabet dataset	93.52%
[12]	Tesseract LSTM	Modified Arabic Dataset	95.45%
[13]	CNN	Handwritten Central Kurdish Isolated characters	96%
Proposed approach	Ensemble Transfer Learning	Handwritten Central Kurdish Isolated characters	97%

made use of as input. And for each additional layer's inputs, that layer's feature maps are utilized.

That's all there is to it; despite how straightforward it may appear, it is essential that in DenseNet, every layer is connected to all the other layers, and this is the core concept that makes it so strong. An input layer in DenseNet is made up of feature maps from earlier layers that have been concatenated [16]. With fewer parameters, DenseNet has been found to perform better than ResNet regarding feature utilization efficiency [17]. However, because concatenation operations are used by DenseNet, a lot of GPU RAM is needed. A memory-efficient implementation developed and can help to alleviate the memory problem. DeseNets offer many beneficial reasons for them to be used, such as improvements in the feature propagation, solving the issue of vanishing-gradient, dramatically decreasing the number of parameters used, and finally, promoting feature reuse. DenseNet's drawback is that the data is copied several times since all the layers are fully connected [18]. DenseNet201 architecture is demonstrated in Fig. 2.

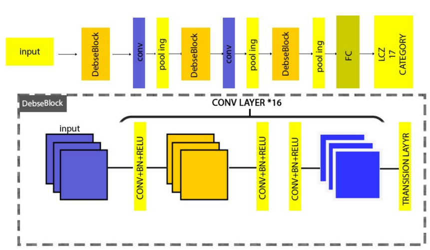

Fig. 2. DenseNet201 Architecture.

C. Xception

As a newer version of the Inception network, the Xception network was introduced. In the Xception model architecture, instead of using typical convolution layers, separable depth-wise convolution layers are used. Within the layers of this model, mapping spatial and cross-channel correlations are included. Leading to the CNN features being completely dissociated. At the same time, the architecture of the Inception network survived a longer period compared to the Xception model. The point of difference is that 14 different modules can be obtained by dividing the 36 convolution layers of the Xception network. After removing the first and last layer, around each layer, there is a continuous residual link. to obtain the cross-channel correlations in an input image. Within each output channel, the input image is converted into spatial correlations. After this process, a convolution method of a depth-wise 1x1 is performed as the relationships can be represented as a 2D+1D map instead of 3D maps. In this model, a 2D space correlation is first implemented, followed by a correlation space of 1D.

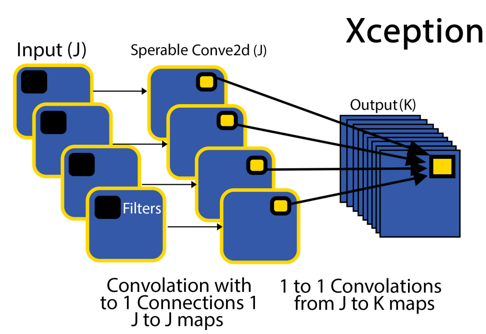

Fig. 3. Xception Architecture.

D. Proposed Ensemble Network

Ensemble learning is typically used to enhance classification problem outcomes by combining several models. Although a collection of classifiers is not always superior to a single top-level classifier, it does decrease the overall gap between misclassified samples and ground truth components. Consequently, it makes sense to provide classifier diversity in order to decrease overall error. By strategically combining independent or negatively linked classifiers, diversity may be attained.

Instead of equally merging the three model's outputs, in the weighted ensemble, we combine the results by determined weight. The product of tensor elements is summed over a single axis, as the one-dimensional vector specifies. The proposed model is shown in Fig. 4. We constructed an ensemble model using three transfer learning models, namely InceptionV3 and Densenet-201, and the Xception model. Each model is separately trained and tested on the dataset. And then combined in an ensemble architecture where average weight is used for the classification purpose, using a weight vector of 0.3, 0.4, and 0.4 corresponding to the models Densene201, InceptionV3, and Xception model.

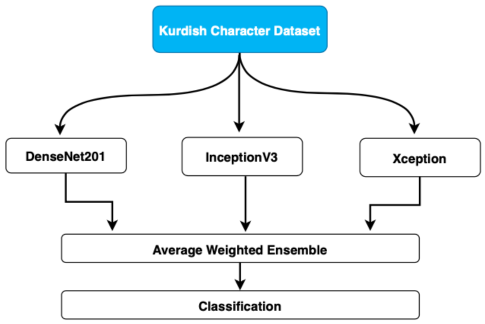

Fig. 4. Proposed Method Architecture.

IV. Experiments

A. Dataset Description

The data source for this study was collected from 390 native Kurdish people in the Kurdistan Region by Rebin et al. [19], whereby the writers are tasked with writing each letter three times in each of three blank blocks that have been provided by the researchers. There are two major groups into which the forms have been distributed: the university students of the University of Kurdistan-Hawler and the academic staff of the Information Technology department at Tishk International University. The dataset contains a diverse set of images for each class, ensuring a comprehensive representation of every Kurdish letter and a total of 40,826 images divided into 35 folders representing 35 classes [20], each corresponding to a Kurdish letter. Image samples of four types of Kurdish letters are shown in Fig. 5 below.
The models were trained to use 70% of data for training and 30% for validation, as shown in Fig 6 The number of images for each character that was used in the testing and training stages is explained in Table II.

B. Data Preprocessing

We have utilized the following preprocessing techniques to preprocess the dataset being used:

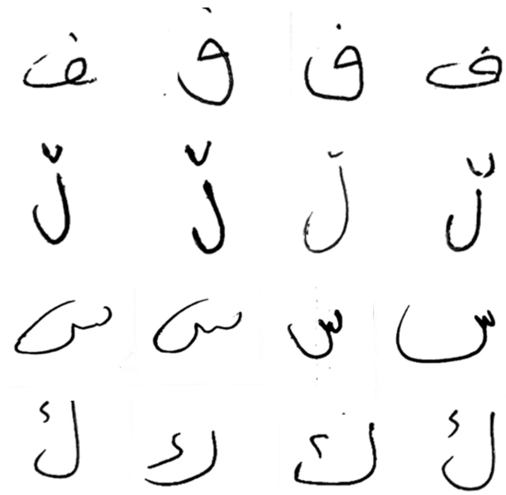

Fig. 5. Image Samples from Dataset.

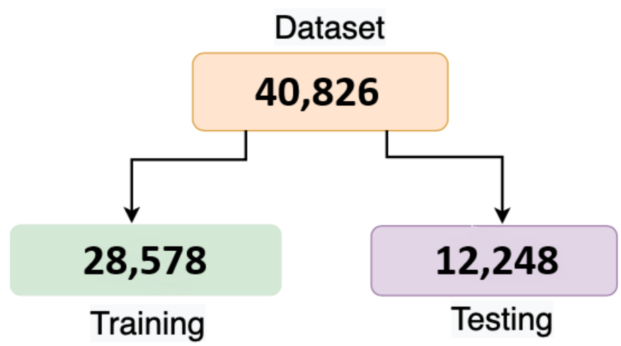

Fig. 6. Dataset Splitting Ratios.

1) Resizing

The images in the dataset are of size 453×459, and all the pictures are resized to the original input size of each model.

2) Normalization

All the pixel values of the images are normalized in the 0-1 range for faster computation.

3) Gray scaling

Given the variation in character coloration within our dataset, owing to the use of differently colored pencils, we employed a grayscale conversion to transform the images from RGB. This approach effectively streamlines the images into shades of gray rather than a strict black-and-white palette.

C. Evaluation Metrics

To accurately evaluate the performance of the ensemble model, the following evaluation metrics are used:

TABLE II. Number of Images Used in Training and Testing Phases

ID	Letter	Total # of images	Test images	Train images
1	ئـ	1134	340	794
2	ا	1134	340	794
3	ب	1134	341	793
4	پ	1008	303	705
5	ت	134	341	793
6	ج	1134	341	793
7	چ	1260	378	882
8	ح	1260	378	882
9	خ	1134	341	793
10	د	1134	341	793
11	ر	1134	341	793
12	ڕ	1134	341	793
13	ز	1512	454	1,058
14	ژ	1134	341	793
15	س	1108	333	775
16	ش	1008	303	705
17	ع	1260	378	882
18	غ	1134	341	793
19	ف	1134	341	793
20	ڤ	1134	341	793
21	ق	1260	378	882
22	ک	1386	416	970
23	ك	883	265	618
24	گ	1134	341	793
25	ل	1134	341	793
26	ڵ	1134	341	793
27	م	1386	416	970
28	ن	1161	348	813
29	هـ	1008	302	706
30	ه	1512	454	1,058
31	و	1134	341	793
32	ۆ	1134	341	793
33	وو	1134	341	793
34	ی	1134	341	793
35	ێ	1134	341	793
Total		**40,826**	**12,248**	**28,578**

1) Accuracy

The accuracy is a measure used to determine the proportion of properly classified predictions [21]. It is represented as follows:

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

2) Precision

Precision is the ratio of accurately anticipated positive outcomes to the total number of properly predicted positive outcomes [21] and may be described as follows:

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

3) Recall

The recall is used to calculate the proportion of properly predicted positive outcomes relative to the total number of outcomes in a given class [21] and may be defined as follows:

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

4) Recall

The recall is used to calculate the proportion of properly predicted positive outcomes relative to the total number of outcomes in a given class [**?**] and may be defined as follows:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

5) F1 Score

The F1 score is the weighted average of accuracy and recall, resulting in a value between 0 and 1. The F1 score is considered a superior performance statistic than accuracy [21] and is defined as follows:

$$\text{F1 Score} = \frac{2\cdot(\text{Recall}\cdot\text{Precision})}{\text{Recall}+\text{Precision}} \tag{5}$$

V. Results and Discussion

Each of the transfer learning models was trained using the Adam optimizer and trained for 40 epochs with a batch size of 64. The models were trained and tested using the Google Colab environment using a Tesla T4 GPU.

Fig. 7 shows the accuracy of both the training and test set of the DenseNet201 model, in which the model has achieved an accuracy of 94% over the test set. Fig. 8 Shows the loss of the DenseNet201 pre-trained model over the 40 epochs on both the training and test sets.

The InceptionV3 model's accuracy was % 95.11 over the test set, as shown in Fig. 9 below.

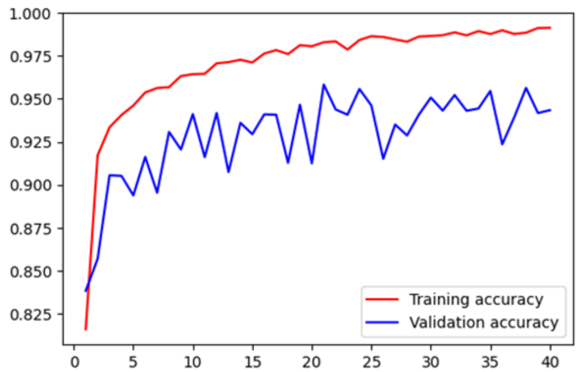

Fig. 7. DenseNet201 Training and Validation Accuracy.

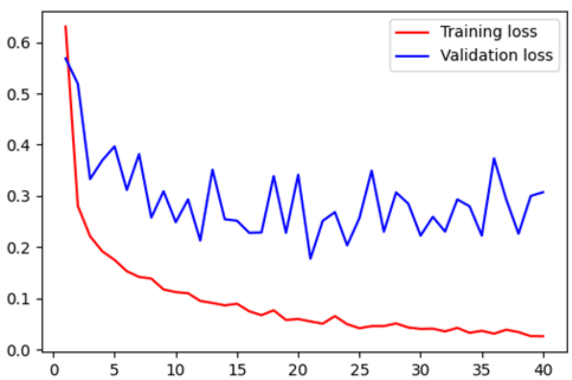

Fig. 8. DenseNet201 Training and Validation Loss.

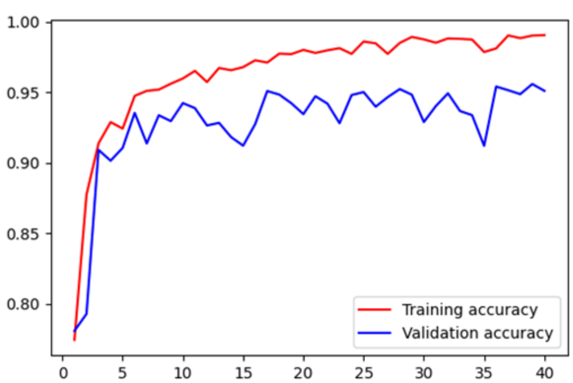

Fig. 9. InceptionV3 Training and Validation Accuracy.

Fig. 10. InceptionV3 Training and Validation Loss.

Fig. 10 Shows the training and validation loss of the InceptionV3 model, in which the training loss is lower than the validation loss expected.

As for the Xception model, it has also achieved an accuracy of 95.56%, as shown in Fig. 11.

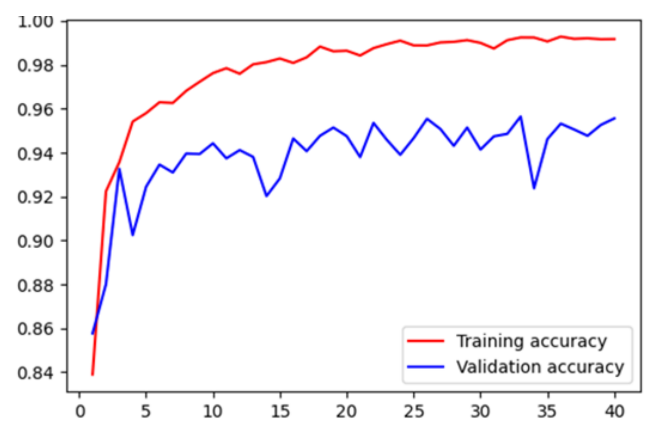

Fig. 11. Xception Training and Validation Accuracy.

The loss of both training and validation phases of the Xception model is illustrated in Fig. 12.

As for the performance of the proposed ensemble model, Fig. 13. shows the confusion matrix, including both the true label and predicted label of the test data. Table III shows the precision, recall, and F1 score of the dataset separately for each letter in the dataset, which are 35 letters in total, along with the overall accuracy, the model performed the best in terms of precision, recall, and F1 score on the letters of "rey qellow" and "beri krawe" achieving 100% on the three metrics. While the letter "elif" had a perfect score in both recall and F1-Score. As for the least performance, the model had some difficulties recognizing the letter "kaf" since it only achieved 88% precision. The letter "hemza" also had a lower

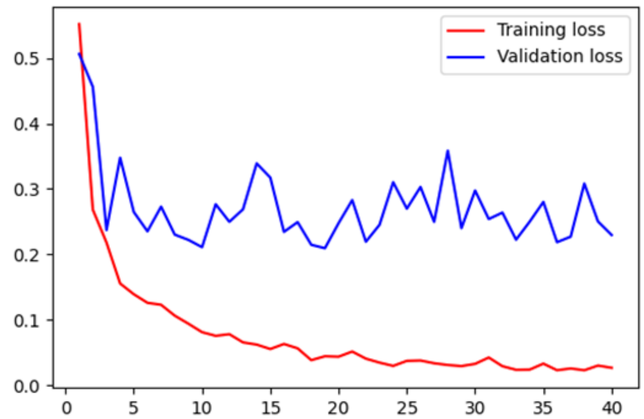

Fig. 12. Xception Training and Validation Loss.

recall score compared to the other letters, where the model had an 88% recall score.

VI. Conclusion

Automatic handwriting recognition is considered a difficult task. In this study, we proposed a weighted ensemble transfer learning approach to recognize Kurdish handwritten letters by using three pre-trained transfer learning models, namely Densenet201, InceptionV3 and Xception, and combining them into a single model using the weighted average ensemble technique. Our ensemble model achieved a very good performance on the Kurdish handwritten character dataset. Any application that needs to recognize Kurdish handwriting can utilize the suggested model, which has a 97% accuracy. It might be utilized as a component of a pipeline that segments Kurdish letters to identify whole words or to recognize characters in foreign languages. The model may be applied in a transfer learning setting.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

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TABLE III. Experimental Results

Character	**Precision**	**Recall**	**F1-Score**
1. hemza ء	0.95	0.88	0.91
2. elif ئـ	0.99	1.00	1.00
3. be ب	0.99	0.99	0.99
4. pe پ	0.99	0.98	0.99
5. te ت	0.96	0.98	0.97
6. ce ج	0.93	0.96	0.95
7. che چ	0.93	0.91	0.92
8. he ح	0.93	0.91	0.92
9. xe خ	0.99	0.99	0.99
10. dal د	0.99	0.98	0.99
11. re ر	0.97	0.99	0.98
12. rey qellew ڕ	1.00	1.00	1.00
13. ze ز	0.98	0.98	0.98
14. zhe ژ	0.99	0.98	0.99
15. sin س	0.99	0.99	0.99
16. shin ش	1.00	0.97	0.98
17. eyn ع	0.96	0.99	0.98
18. xeyn غ	0.99	0.97	0.98
19. fe ف	0.98	0.92	0.95
20. ve ڤ	0.96	0.95	0.95
21. qaf ق	0.91	0.96	0.93
22. kaf ك	0.98	0.95	0.96
23. kaf ک	0.88	0.94	0.91
24. gaf گ	0.90	0.98	0.94
25. lam ل	0.98	0.99	0.98
26. lami qellew ڵ	0.99	0.99	0.99
27. mim م	0.99	0.97	0.98
28. nun ن	0.98	0.95	0.96
29. he هـ	0.99	0.99	0.99
30. ser ه	0.97	0.99	0.98
31. waw و	0.97	0.98	0.98
32. wawi qucaw ۆ	0.99	0.99	0.99
33. beri krawe وو	1.00	1.00	1.00
34. ye ي	0.98	0.98	0.98
35. jeri krawe ێ	0.99	0.99	0.99
Accuracy	0.97		

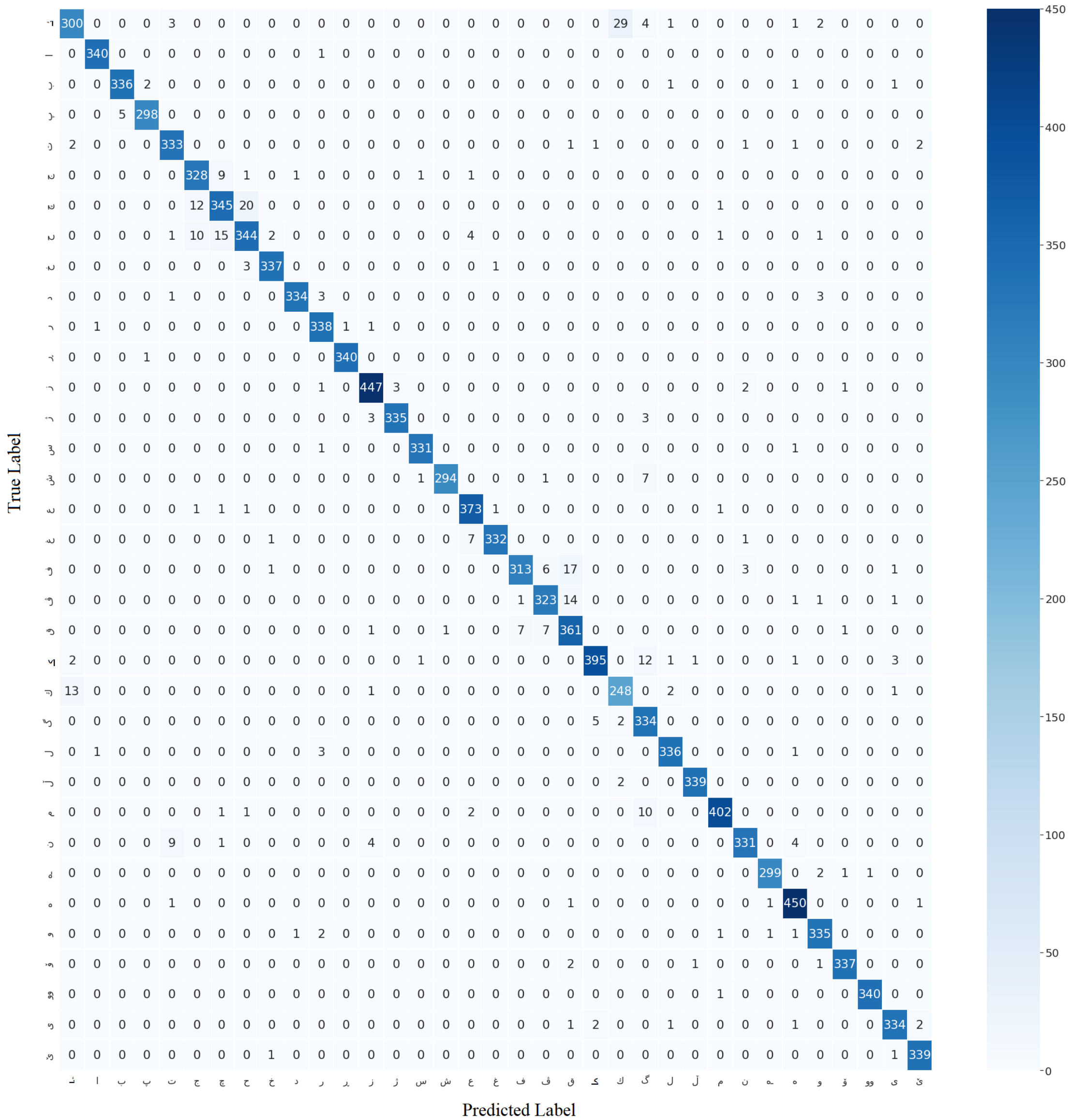

Fig. 13. Proposed Ensemble Model Confusion Matrix

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