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RESEARCH ARTICLE

TILPDeep: A Lightweight Deep Learning Technique for Handwritten Transformed Invariant Pashto Text Recognition

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ABSTRACT Pashto is the native language of Afghanistan and one of Pakistan's most essential and regional languages. The Pashto language has a vast number of native speakers who live in various parts of the world. The handwritten Pashto textual trajectories are hard to recognize and detect due to the cursive style and handwriting variation. The transformation behaviour, i.e., scaling, rotation, and shifting of handwritten text, are the prominent but challenging factors. A lightweight deep learning-based model construction for low and medium-resource devices in a less-constrained environment is challenging. This paper provides a practical, light deep learning-based model for predicting handwritten Pashto words. A massive Pashto-transformed invariant inverted handwritten text dataset is prepared with the help of the Pashtun community. A lightweight MobileNetV2 has been highly tuned for Pashto handwritten text classification, extracting images' features (MoI). We inverted the dataset to make the model more accurate and restrict it to fifteen epochs. Extensive experiments have been conducted to validate the suggested model's performance. The proposed transformed invariant lightweight Pashto deep learning (TILPDeep) technique achieves a training accuracy of 0.9839 and a validation accuracy of 0.9405 for transformed invariant Pashto handwritten inverted text using recognition matrices.

INDEX TERMS Pashto handwritten inverted text recognition, lightweight deep learning, transformation invariant text, low resource and touch sensitive devices, unconstraint environment.

I. INTRODUCTION

Pashto is a regional cursive language spoken in Pakistan and the national language of Afghanistan, and all the native speakers of this language are called Pashtun. It is an ancient language; hence, the origin and date of birth are unknown. However, it is the cultural heritage of the Pashtun community. The Pashto-speaking area is important due to its crucial global geographical position. The historical theories show conflicts regarding the foundation of the Pashto language because documents are unavailable.

خ	ح	څ	چ	ځ	ج	ث	ټ	ت	پ	ب	ا
ص	ښ	ش	س	ږ	ژ	ز	ړ	ر	ذ	ډ	د
ن	م	ل	ګ	ک	ق	ف	غ	ع	ظ	ط	ض
				ئ	ۍ	ی	ې	ي	ه	و	ڼ

FIGURE 1. Pashto language characters.

The Pashto language has 44 characters, which are given in Fig. 1. These characters are taken from Arabic and Parso-Arabic character sets.

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The declaration of Urdu as the primary medium of education in public schools is a systematic degradation and deterioration of many of Pakistan's native languages, including Pashto [1]. It has caused increasing resentment amongst Pashtuns, who complain that Pashto is always publicly neglected [9], [10]. The Pashto language will become obsolete due to less attention from the Pakistani government. The Pashto language will become obsolete due to less attention from the Pakistani government. The new generation of Pashtuns is also less interested in speaking and writing because the Pashto language is slowly and gradually eliminated from the school curriculum.

Computers and smartphones are now everywhere and common in Pashtun families. Computers and smartphones have revolutionized the way we work and imitate humans. Words recognition and detection is a natural gift for humans by the Creator. Humans try to mimic the human with computer machines and transfer the human ability to recognize, classify, and detect words. However, the computer machine will not be able to beat human capacity. The detection and recognition of handwritten text produce difficulty even for humans who use contextual, discourse, and domain knowledge. Handwritten text classification, recognition, and detection are essential branches of pattern recognition, computer vision, and natural language processing that emulate human capabilities in computer machines. This task becomes more challenging, complex, and vital if geometric variations are involved with Pashto handwritten text. The critical applications of Pashto handwritten text classification, recognition, and detection are given in the following,

Handwritten text detection in old books (مخطوطات), i.e., Rahman Baba, Khushal Khan Khattak books.

- Unknown old handwritten books.
- Automatic detection and recognition of old handwritten text on national ID cards.
- Handwritten text detection and recognition on Form B.
- Handwritten Pashto text recognition and detection on domicile.
- Handwritten Pashto archive text written via stylus pen or fingers on tablets or smartphones.
- Handwritten Pashto textual posts and comments detection and recognition on social media.
- Handwritten Pashto text on the envelope and in letters.

Nowadays, deep learning and transfer learning techniques are prevalent in image processing, computer vision, natural language processing, pattern recognition, etc. Deep learning and transfer learning computation require more time to conclude than conventional machine learning techniques. The GPUs have resolved this classification, recognition, and detection problem. Traditional machine learning and deep learning techniques are subject to the type of problem and the goal to achieve. We believe deep learning-based models are still weak compared to human visual perception. However, deep learning and transfer learning-based techniques are better than conventional machine learning techniques. The objectives to achieve and the problems to face are given in the following.

1. The first objective of this study is to develop a deep learning technique for recognizing Pashto handwritten words, which has not been done yet.
2. The technique should be lightweight and suitable for low-resource devices in unconstraint situations.
3. Create a complete Pashto handwritten words dataset consisting of all possible words constructed from two characters. It is an evolutionary process, and we aim to develop a complete dataset of Pashto handwritten words.
4. The dataset should contain a good ratio of geometric variated words, i.e., rotation, scaling, and shifting.
5. Different people have different handwritten variations, so the shape becomes different for the same word.

As mentioned above, several Pashto handwritten characters datasets are constructed, but the Pashto handwritten words dataset is unavailable, and we know it after a lengthy investigation and search. We developed a Pashto handwritten transformed invariant words dataset, which took six months. Students, teachers, and ordinary people of Pashtun society were engaged in developing the handwritten dataset. Engaging many people has the benefits of different writing styles and transformed variation. Some images from the constructed handwritten Pashto transformed invariant dataset have given in Fig. 2.

FIGURE 2. **Pashto handwritten transformed invariant words.**

The existing deep learning-based techniques impose constraints on a writer to a baseline with a specific direction and rotation. Writing text of identical length and width with a particular amount of rotation in a predetermined location is tough. The existing techniques, i.e., ResNet, GoogleNet, VGG16, VGG19, and DensNet, etc., also took a massive amount of time in training, validation, and testing, therefore not feasible Pashto handwritten text. The proposed deep learning-based technique provides a reasonable solution for recognizing Pashto handwritten text for low-resource devices.

The remaining paper is divided into sections as follows.

Section II presents the literature review, section III elaborates the proposed technique, section IV discusses the experimental results, and section V concludes the proposed technique.

II. RELATED WORK

For the last four decades, handwritten text prediction has been explored, and various researchers have created specific Techniques. Most of these methods are developed to predict words for a particular language [4]. These methods fail to achieve high accuracy when identifying words that are rotated, shifted, or scaled somewhat. Similarly, these systems impose a specific writing style, preventing them from experimenting with different handwriting scripts [5]. These limitations apply to words written on the baseline, ascender, and descender.

The majority of Arabic and Perso-Arabic character recognition systems, which classify and recognize characters with the help of different features [6], use machine-learning methods (MLT) [7]. For cursive script, Artificial Neural Network (ANN)-based techniques have been proposed in the literature [6], [8], [9], and [10], in which Feed Forward Neural Networks (FNN) and Back Propagation Neural Networks (BNN) are used as classifiers. These techniques have been applied to attain high accuracy independent of the system's resources and time. These systems have problems with geometrical variant words, such as shifting, scaling, and rotating, and forcing the user to write on the ascender, descender, and baseline while writing. Because of these limitations, the system is hard to operate on portable devices such as smartphones and tablets.

Handwritten text recognition techniques have used Support Vector Machine (SVM) [11], [12], [13], [14], [15], [16]. A linear SVM uses an ideal separating line to distinguish two classes of objects. Similarly, multi-class handwritten text classification has been performed by altering SVM to construct a hyper-plane using support vectors to detect margins. The techniques mentioned above have problems of taking massive time to converge. Low resource devices and invariant transformation words are the shortcomings of these SVM-based approaches.

For handwritten text recognition, the Naive Bayes method has been used in [17], [18], [19], and [20]. A naive Bayes classifier is comparatively efficient for large data classification in historical and handwritten documents. On the other hand, these systems cannot recognize geometric invariant long handwritten words. Due to writing limits, these methods are also complicated for the average user to utilize.

Rule-based approaches for handwritten characters and word recognition have been proposed [4], [7], [20], [21], and [22]. The disadvantage of Rule-based approaches is that they are reliant on the baseline. In these systems, invariant transformed words are not considered for prediction. These methods necessitated many classification and recognition criteria, which might be difficult to handle when an error or bug is found. The weighted linear classifier is also employed with local features in [23], where weights are applied to each extracted feature vector. This approach is also unable to handle transformation variations.

For handwritten character recognition, a large number of systems employ the Hidden Markov Model (HMM) technique [21], [24], [25], [26], [27], [28], and [29]. Due to the probabilistic strategy of transitioning from one state to another, these techniques have a lower time complexity than other state-of-the-art techniques. These methods are incapable of recognizing rotated, scaled, or shift-invariant characters. Due to handwriting limits, these approaches are cumbersome for the average user. Furthermore, word prediction for low-resource devices is not addressed.

In the literature, template-matching approaches are also employed for character recognition [30], [31], [32], [33], [34], [35]. Transformation, invariant templates of handwritten characters and words, are not addressed. Minor changes in the templates mismatch the whole character and word. All the mentioned research work above is designed for character recognition. These systems store templates for each character, which consume ample memory space. Furthermore, these techniques are unsuitable for low-resource devices in an unconstrained environment.

Deep learning techniques are highly recommended for handwritten text prediction and document analysis [19], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54]. The deep learning models used for Pashto handwritten characters, words, and Pashto text lines are discussed in [39], [43], [46], [50], [55], [56], and [57]. The authors in the paper [46] present a dataset of 17015 images, each consisting of a full-text line. To evaluate the performance, they predict Pashto text from images using Bidirectional and Multi-Dimensional Long Short Term Memory (BLSTM and MDLSTM). This work is limited to a single line, and the error rate is 9.22%.

Authors in the paper [55] described that a real dataset is created manually. They further stated that manually creating a dataset is an uphill task. They propose a semi-automated procedure for producing Pashto document images using LSTM. They used 1000 images having Pashto ligatures and claimed to reduce the production interval by three times that of the manual method. This paper is not concerned with detecting, classifying, and recognizing Pashto text.

A Pashto character recognition system and dataset ''Poha'' are proposed in [43]. This paper uses a convolutional neural network CNN model to recognize Pashto handwritten characters. In the pre-processing phase, they use the deep fusion image processing method. They claim that their system achieves a test accuracy of 99.64% for Pashto Handwritten character recognition. The transformation variation is not discussed that either they consider it or not. Furthermore, this work is limited to character compared to many words.

In the paper [56], the authors claimed that cursive script segmentation into characters is a challenging problem. They try to develop single-stroke ligatures as recognizable and generate a corpus of 2313736 Pashto words. They find out 19268 unique ligatures in the Pashto cursive script.

They perform an analysis, showing that 7000 ligatures symbolize 91% of the corpus. They also identified about 7681 primary ligatures, representing the primary shapes of all the ligatures. It means that they identified 7681 unique primary ligatures. The automation section in generating printed ligatures for Pashto text has been achieved using LSTM.

In the paper [39], the authors present research on Pashto character recognition. They claim that the cursive script domains for research are still an open and challenging task, especially in the Pashto language, using machine-learning algorithms. They further claim that a slight change in characters changes the characters entirely. Another reason the Pashto language is difficult to process is a large number of characters in its characters set. They proposed a technique for recognizing Pashto isolated characters, using multiple long short-term memory (MLSTM) as a classifier. They also use the decision trees and zoning function for classification to cope with invariant moments. Total accuracy of 89.03% has been achieved by using MLSTM, while recognition rates based on decision trees (DT) are 72.9%. They further claim that they achieved 74.56% accuracy with the help of a zoning feature vector and 74.56 for invariant moments-based feature maps. The proposed system's applicability has been assessed using confusion matrix accuracy and f-score.

A ligature-based Pashto recognition system has been proposed in a research work [50] composed of different transfer learning techniques. They use an existing dataset named FAST-NU, which uses AlexNet, GoogleNet, and VGG as pre-train classifiers on Pashto printed ligature. The accuracy achieved by AlexNet is 97.24, GoogleNet is 97.46, and VGG is 99.03 for printed Pashto ligatures.

Rehman et al. [57] published research on Pashto handwritten character recognition. They used three deep learning models, i.e., CNN, LeNet, and Deep CNN. The geometric transformation and handwritten variation are not addressed clearly in this research. However, most deep learning techniques can handle the variation up to some level. They claim that Deep CNN for Pashto characters and digits recognition achieved high accuracy compared to LeNet and CNN.

One of the recent Pashto handwritten datasets was published in [37] called Pashto Handwritten Text Imagebase (PHTI). The authors do arduous work to develop Pashto handwritten text line dataset. Furthermore, they engage 200 males and 200 females at the writing stage. After segmenting the handwritten text pages of 4,000, they came up with 36,082 images. Each image has a Pashto text line, similar to the Gold Standard Pashto dataset [58]. However, the Gold Standard Pashto dataset is composed of printed text. The author annotates/labels each textual image with UTF-8 code. However, this dataset differs from the developed handwritten Pashto words dataset proposed in this paper, which is discussed in the paper below.

Table 1 shows a detailed summary of the existing techniques concerning five parameters, in which no single technique meets all five parameters. The key attention of researchers is the high accuracy of text either in real-time or from images, as shown in Table 1. However, accuracy is not the only objective to achieve. The technique must be feasible to run on low and medium-resource devices. In contrast, the existing deep learning techniques face issues with low to medium-resource devices in both the training and validation phases. Furthermore, transformation variations of handwritten Pashto words also need to be explored.

III. THE PROPOSED APPROACH

This section explores Deep learning techniques for handwritten Pashto words classification and prediction with low computational cost and reasonable accuracy. For this purpose, MobileNetv2 has investigated Pashto's handwritten text processing in much detail. The selection of MobileNetv2 for Pashto handwritten text is due to the idea of the manifold of interest (MoI) and inverted residual Bottleneck. The handwritten Pashto text occupied an image's small area (MoI) with helpful information, as shown in Fig. 3.

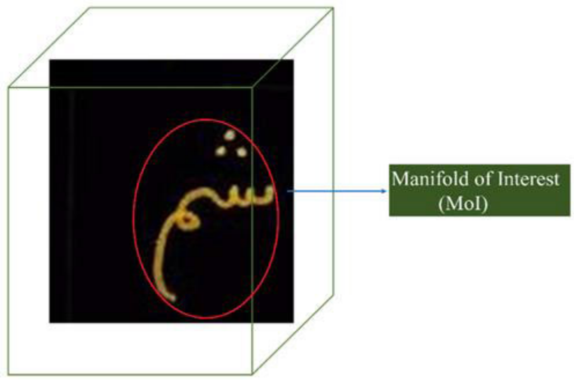

FIGURE 3. (MoI) area enclosing the red circle.

As for as Pashto's handwritten text is concerned, the idea of MoI is suitable due to the tiny handwritten trajectory. Color and background have no valuable and vital information to improve accuracy in handwritten text processing. However, different experiments have been conducted regarding channels to find the optimal value of α, which is the number of optimal dimensions for Pashto handwritten text. The hyperparameter α is a number that controls the convolution layer's depth or shrinks the output channels in output activation, i.e., $\alpha = 0.5$ means 64 channels while $\alpha = 1$ means 128 channels. If the number of channels decreases, lost information in the MoI increases by using ReLU, but if the number of channels increases, information lost in the MoI decreases.

The Rectified Linear Unit (ReLU) is an activation function in the proposed technique, a non-linear price-wise activation function. The ReLU activation function (1) is linear for values greater than zero and non-linear for negative values, as shown in Fig. 4, which also lost some information. The advantages of using ReLU are simplicity and sparsity, which is more effective in deep learning techniques with huge computation

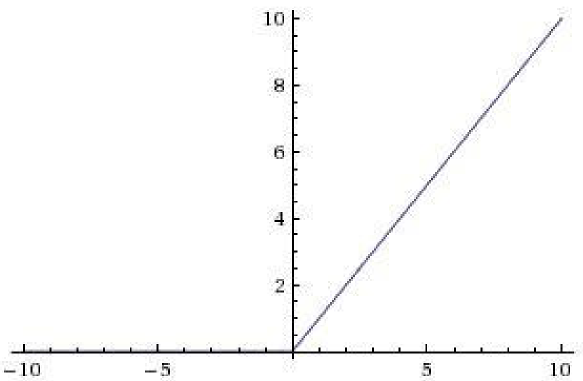

FIGURE 4. ReLU activation function for positive and negative values.

compared to Sigmoid and Tanh.

$$f(x) = \begin{cases} x & if\ x > 0 \\ 0 & if\ x < 0 \end{cases} \quad (1)$$

To cope with information lost due to ReLU and MoI, i.e., low-dimension activation, MobileNetv2 comes with a unique idea of a new block called "Inverted Residual with a Linear Bottleneck." The "Inverted Residual linear bottleneck" block is given in Fig. 5.

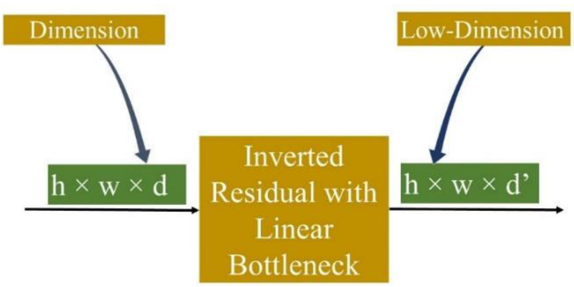

FIGURE 5. Block diagram of inverted residual with linear Bottleneck.

In Fig. 6, the term $(h \times w \times d)$ is the input Pashto handwritten text image of height h, width w, and dimension d. The first operation is the pointwise convolution followed by batch normalization and ends with ReLU activation. The output of the first layer is input for the second layer, which starts from depthwise convolution followed by batch normalization with ReLU as an activation function. The output of the depthwise convolution layer is the input for the pointwise convolution layer. A pointwise convolution operation takes place in this layer, proceeding to batch normalization. The output of the last layer $(h/s \times w/s \times d')$ has a low dimension and is more compressed as compared to $(h \times w \times d)$. A residual connection is added at the end, which adds the model's output and input to increase the accuracy.

Batch normalization is used to normalize data distribution, i.e., center $= 0$ and standard deviation 1, as shown in Fig. 6. The detail of each step and operation of Fig. 6 is defined in the following.

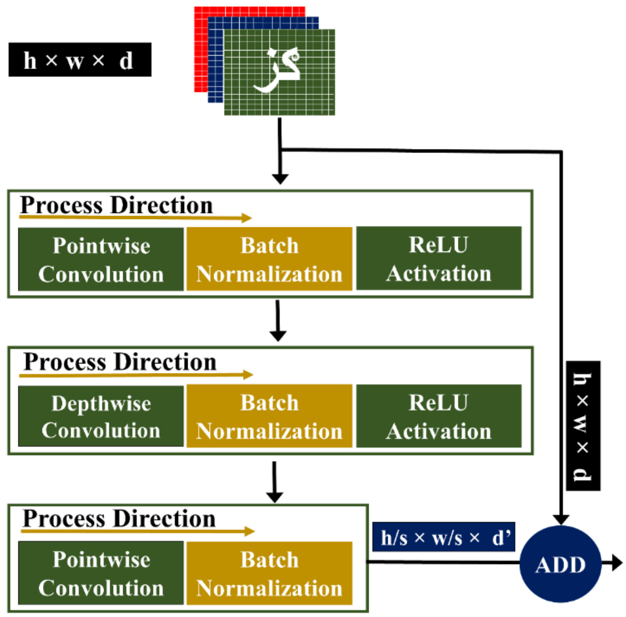

FIGURE 6. Inverted residual with linear bottleneck for Pashto handwritten text.

A. DEPTHWISE CONVOLUTION

In depthwise convolution, the operation is performed on a single image channel containing Pashto handwritten text at a time. The depthwise convolution is different from the standard convolution shown in Fig. 7.

In depthwise convolution, one kernel is required for one channel. Hence, the required N kernels and the number of N are equal to the number of M for the entire input image volume. By stacking all blocks or units of depthwise convolution, the result is $\mathrm{Dg} \times \mathrm{Dg} \times M$. The number of multiplication operations for each block $(\mathrm{Dk} \times \mathrm{Dk})$ is Dk^2; for one channel, the number of multiplication is $\mathrm{Dk}^2 \times \mathrm{Dg}^2$. The total number of multiplications for M filters is $M \times \mathrm{Dk}^2 \times \mathrm{Dg}^2$.

B. POINTWISE CONVOLUTION

The pointwise convolution performed a linear combination at each of the M layers of the image composed of handwritten Pashto words. The input is $\mathrm{Dg} \times \mathrm{Dg} \times M$ shape while the kernel is $1 \times 1 \times M$, which performs a 1×1 convolution operation overall M layers, as shown in Fig. 8.

The output size is the same as the input size, i.e., $\mathrm{Dg} \times \mathrm{Dg} \times N$. There are M multiplications for one operation and $\mathrm{Dg} \times \mathrm{Dg} \times M$ operation for one kernel. The number of multiplications in pointwise convolution is $N \times \mathrm{Dg} \times \mathrm{Dg} \times M$.

C. BATCH NORMALIZATION

The batch normalization is an important property of convolution neural networks and defined twice in MobileNetv2 architecture, which is very efficient for Pashto handwritten text trajectories. When the range and variation in data are large, the training model takes more time to converge. Batch normalization fixed such data in a small

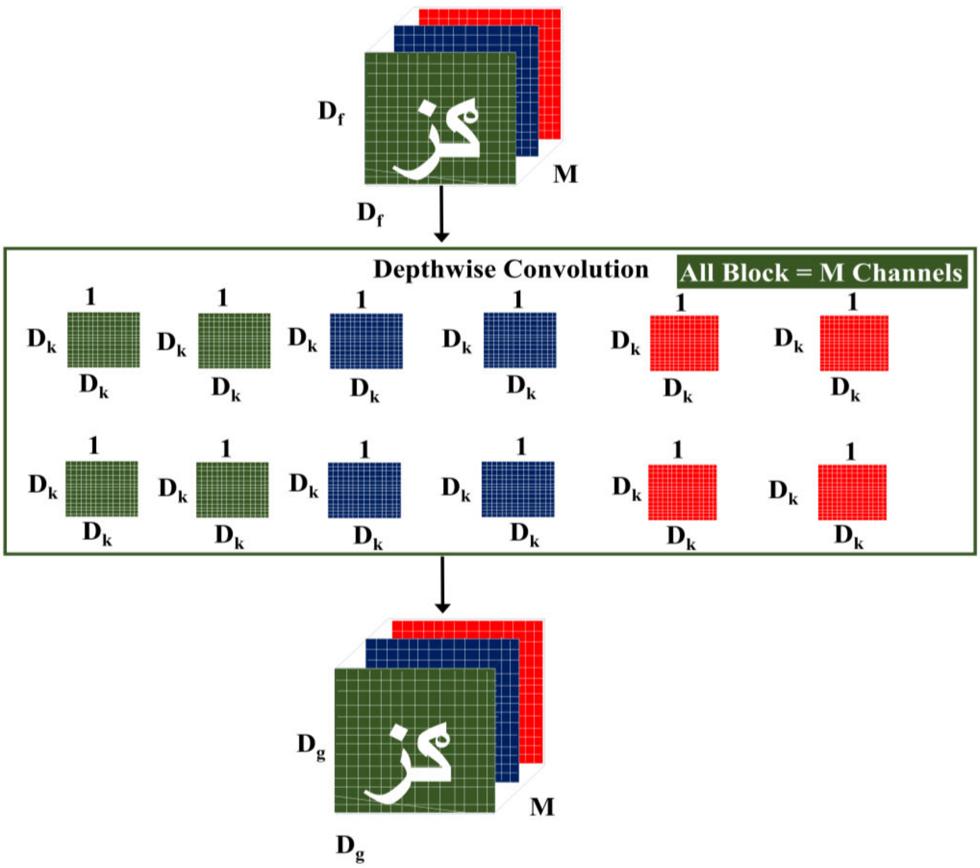

FIGURE 7. Depthwise convolution operation.

range to help the training model to converge quickly. Batch normalization also plays a role in model regularization by dropping some neurons. Batch normalization is performed with the help of the following equations.

$$\mu = \frac{1}{m}\sum_{i} x^{i} \tag{2}$$

$$\sigma^{2} = \frac{1}{m}\sum_{i} (x^{i} - \mu)^{2} \tag{3}$$

In (2), x^i is the input values, m is the total number of values, and μ is the mean of the input. In (3), μ is the mean; x^i are input values, m is the total number of input values and σ^2 is variance. In batch normalization, the two activation values, i.e., μ and σ^2 are determined and then normalized the activation values for input xi as $x^{i}_{normalization}$ by using (4). It is the reason that each neuron output across the batch has normal standard distribution. In (4), ϵ is the numerical constant used in case of zero variance (σ^2).

$$x^{i}_{normalization} = \frac{(x^{i} - \mu)}{\sqrt{\sigma^{2} - \epsilon}} \tag{4}$$

The whole layer's output $\hat{x}$ is the final calculation using (5), in which linear transformation occurs with two trainable parameters, γ, and β. The first trainable parameter, γ is used to adjust the standard deviation, while β is used to move the data curve toward the right or left side, as shown in Fig. 9.

$$\hat{x} = \gamma \times x^{i}_{normalization} + \beta \tag{5}$$

D. RESIDUAL CONNECTION

The approach taken by MobileNetV2 is **thin** $\longrightarrow$ **thick** $\longrightarrow$ **thin**, as shown in Fig. 10. The first layer, 1×1 convolution, is thin, making the networks wider in a row. The depthwise 3×3 convolution already reduces the parameters to increase the computation speed. The last layer performed 1×1 convolution and squeezed the network to make equal dimensions initial and final output. This Residual-based CNN model is different, fast, and lightweight due to the 1×1 pointwise convolution [41], which performs compression or encoding. In standard residual convolution, the sequence is **thick** $\longrightarrow$ **thin** $\longrightarrow$ **thick**, and in the MobileNetV2, the residual convolution is **thin** $\longrightarrow$ **thick** $\longrightarrow$ **thin**, which is why it is called inverted.

The model used in the proposed technique for Pashto handwritten word prediction starts from a thin input layer with linear activation and ends with a thin output layer with linear activation. This model is faster than other CNN-based models

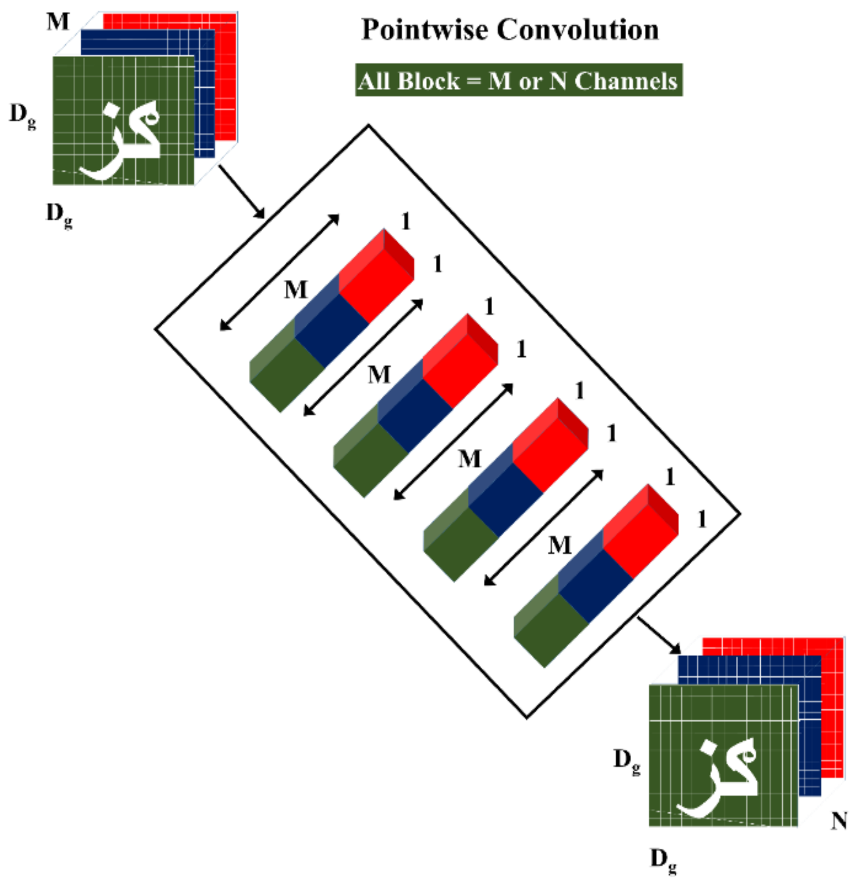

FIGURE 8. Pointwise convolution operation.

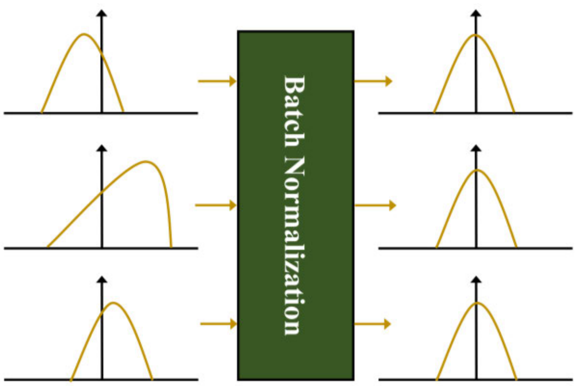

FIGURE 9. Batch normalization.

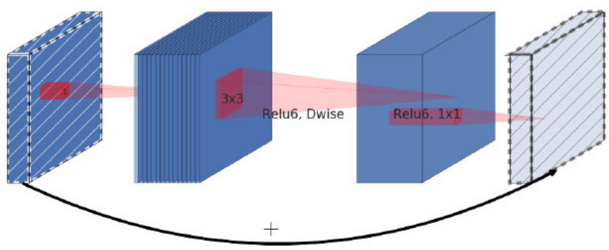

FIGURE 10. Inverted residual with linear Bottleneck.

due to the low dimension or compression [41]. The inverted residual property in the proposed technique has increased the accuracy and performance. If the number of channels $d = d'$ with stride $s = 1$, the dimension in input and out will be the same. However, the dimension or channel will be reduced if $d' > d$ with stride $s = 2$ or more.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The dataset used for experimentation is the enhanced version of the dataset mentioned in [42], in which we discover more classes, and the number of classes is extended from 541 to 936. The dataset's name is also changed from PHWD-V1 to Pashto Handwritten words, version 2 (PHWD-V2). Two variants of the Pashto handwritten text dataset are prepared, i.e., RGB images with white background, as shown in Fig. 11 and an inverted version of that dataset, as shown in Fig. 12. The dataset has 936 classes, each consisting of 100 different variant samples. Table 2 illustrates statistics on the developed dataset (PHWD-V2). In the dataset PHWD-V2, five male and five female teachers were involved. Similarly, thirty male and thirty-eight female students were engaged in the handwriting phase. Twenty males and two females from the common people category participated in the generation of PHWD-V2.

TABLE 1. Summary of several handwritten Pashto text processing techniques.

Techniques	Pashto Handwritten Words Recognition	Geometric Variation	Lightweight classifier	Deep Learning Based Classifier	Accuracy in %
[5]	No	Unknown	No	No	93.5 %
[6]	No	No	No	No	Not Clear
[8]	No	No	No	No	96 %
[9]	No	No	No	No	96.7 %
[10]	No	No	No	No	98.6 %
[12]	No	No	No	No	2.8 % Error Rate
[13]	No	No	No	No	92.4 %
[14]	No	No	No	No	99.7 %
[15]	No	No	No	No	92 %
[16]	No	No	No	No	9.3 % Error Rate
[18]	No	Yes	Yes	No	97.5 %
[20]	No	No	No	Yes	97.3 %
[22]	No	No	No	No	96 %
[23]	No	No	No	No	98.2 %
[24]	No	No	No	No	90 %
[25]	No	No	No	No	16.3 % Error rate
[26]	No	No	No	No	2 % Error Rate
[27]	No	No	No	Yes	74 %
[28]	No	No	No	No	95.7 %
[29]	No	No	No	No	89 %
[30]	No	No	No	No	91.5 %
[32]	No	No	No	No	97.2 %
[33]	No	No	No	No	89.2 %
[34]	No	No	No	No	92.8 %
[35]	No	No	No	No	83 %
[59]	No	No	No	No	87.6 %

TABLE 2. Statistic on PHWD-V2.

# of classes	Samples Per class	Teachers		Students		Common People		Total Male	Total Female
		Male	Female	Male	Female	Male	Female		
936	100	5	5	30	38	20	2	55	45

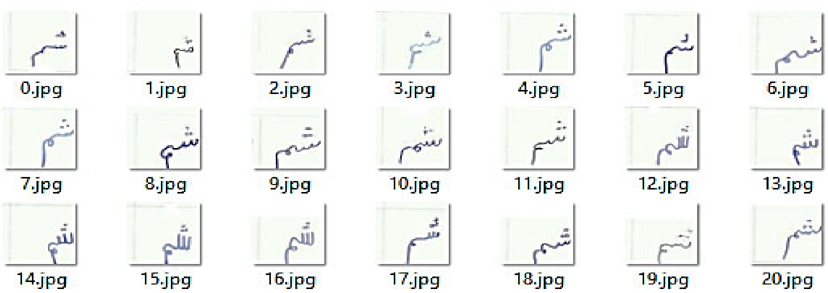

FIGURE 11. Partial View of Pashto handwritten RGB dataset.

The proposed technique has exploited the lightweight deep learning-based approach to predict and recognize Pashto handwritten text. MobileNetv2 with different configurations has been manipulated during experiments to best model selection for Pashto handwriting text prediction and recognition. Detail on the experimentation of

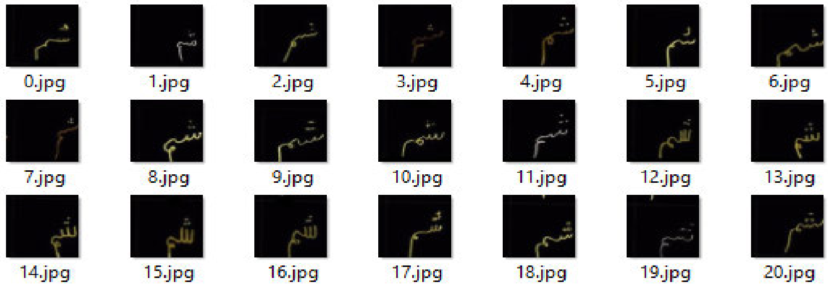

FIGURE 12. Partial view of inverted Pashto handwritten dataset.

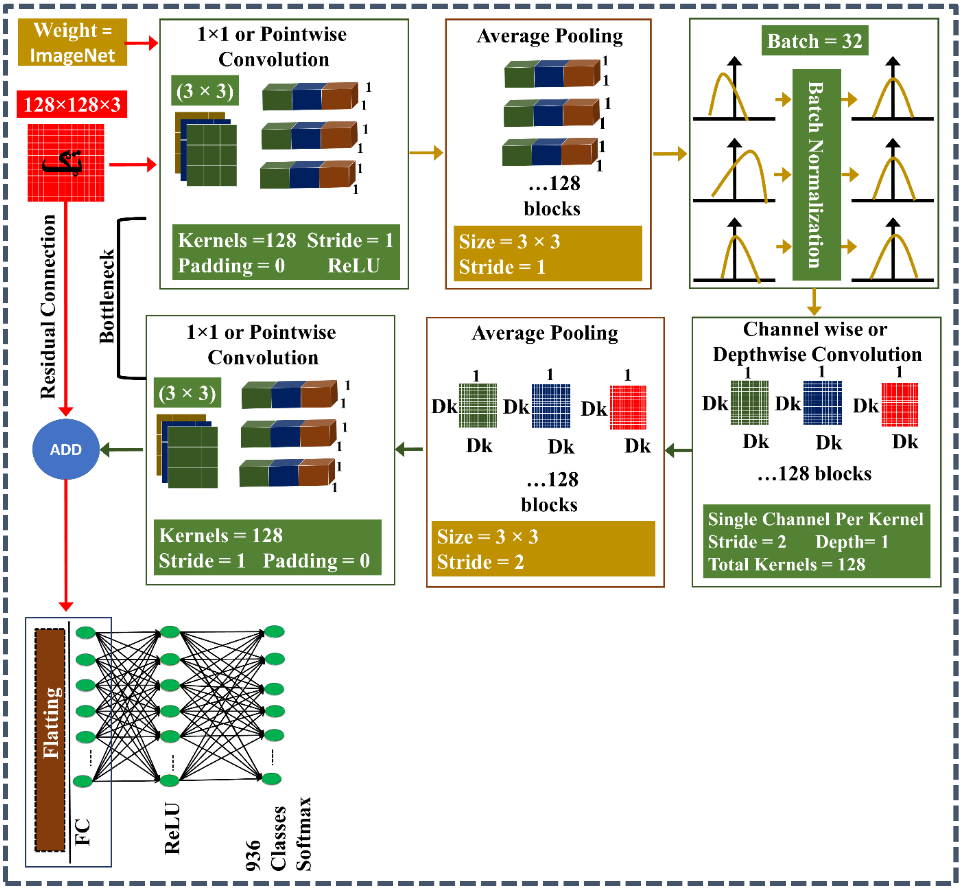

FIGURE 13. MobileNetV2 based Model_1.

different models based on MobileNetv2 is given in the following.

For experimentation, the dataset has been split into two parts, i.e., 80% and 20%, for the training and prediction phase, respectively. The first experiments on Pashto handwritten RGB Dataset have been performed on NobileNetV2 "Model_1," shown in Fig. 13. In Model_1, the batch size is 32, epochs are 20, the number of kernels is 128, dropout is 20%, the optimizer is Adam, the last layer activation is softmax, and the base learning rate is 0.001. Model_1 has one input layer, which takes Pashto handwritten word images of size 128 × 128 × 3. This model extracts 3,457,000 parameters, of which 2257984 are dropout by the dropout layer, and the remaining 1199016 are used in the dense layer for 936 classes.

Model_1 achieves a training accuracy of 0.8370 and a prediction accuracy of 0.6570. Similarly, the loss in training accuracy is 0.163, and the loss in prediction accuracy is 0.343. The training and prediction accuracy is demonstrated in Fig. 14, and the losses in training and prediction are presented in Fig. 15.

In the training and prediction phase, Model_1 does not perform well to achieve an efficient result, as shown in Fig. 14. The losses shown in Fig. 15 for both the training and prediction phase are also high, indicating that this model is unsuitable for commercial applications. The reason for

TABLE 3. Comparison of the proposed technique with other lightweight deep learning techniques for Pashto handwritten text recognition.

Techniques	Pashto Handwritten Words Recognition	Geometric Variation	Lightweight classifier	Deep Learning Based Classifier	Dataset	Accuracy in %		
						Training	Validation	Testing
Proposed Technique	Yes	Yes	Yes	Yes	PHWD-V2	98.39 %	94.05 %	94.05 %
[19]	No	Yes	No	Yes	9 datasets			99.74 %
[27]	No	Yes	No	Yes	English			74%
[37]	No	Yes	No	No	PHTI	NON	NON	NON
[39]	No	Yes	No	Yes	Own Dataset	89 %	72 %	
[41]	No	Yes	No	Yes	FAST-NU	97.24 %	97.46 %	99.03 %
[43]	No	Yes	No	Yes	Poha			99.64 %
[46]	No	Yes	No	Yes	KPTI			9.22 % Error
[50]	No	Yes	Different classifier	Yes	FAST-NU			99.3 %
[54]	No	Not clear	No	Yes	DISEC'13 Tobacco800 KPTI			90.78 %

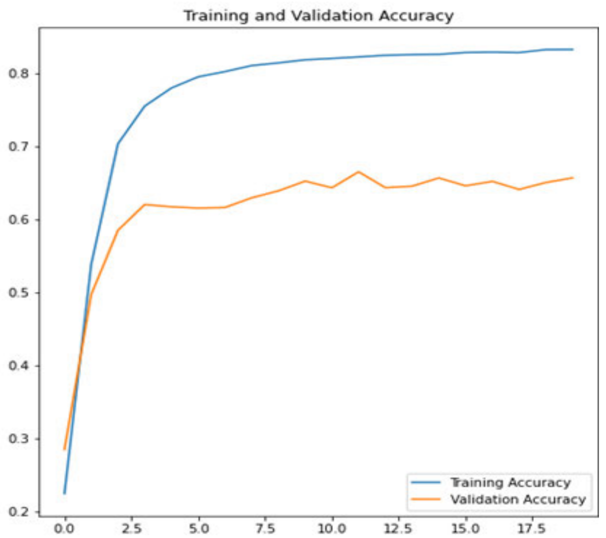

FIGURE 14. Training and prediction accuracy of Model_1.

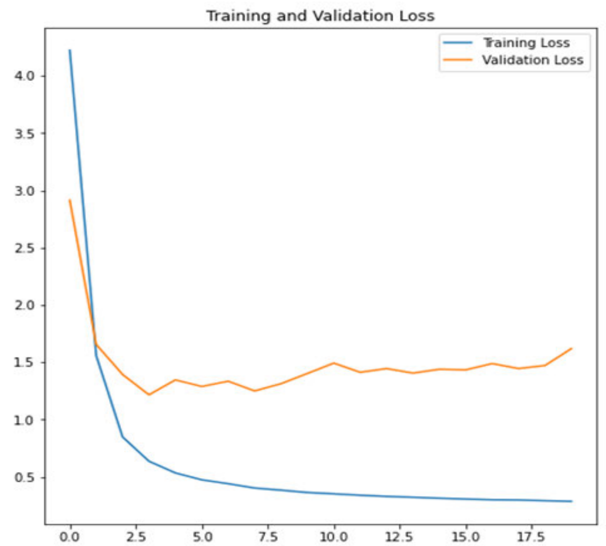

FIGURE 15. Training and prediction losses of Model_1.

not efficiently converging Model_1 is the white pixels in the background. As a result, the model considers the white background data for training and prediction, and the dropout layer drops most of the actual stroke trajectory pixels.

Another model called Model_2 is configured with a bit of change to increase the training and prediction accuracy and decrease the losses, as shown in Fig. 16. We also inverted the dataset, which is shown in Fig. 12. The inverted dataset has split into two parts, i.e., 20% and 80%, for the prediction and training phases, respectively.

In Model_2, the kernels are 128, epochs are 20, the batch size is 32, dropout is 20%, the optimizer is Adam, hidden layer activation is ReLU, the last layer activation is softmax, and the base learning rate is 0.001. Model_2 has an input layer, which takes Pashto handwritten word images of size $117 \times 117 \times 3$. The total parameters extracted are 3,457,000, of which 2257984 parameters are dropouts, and the remaining 1199016 are used in dense layers for 936 classes.

The training and prediction accuracy achieved by Model_2 is 0.9871 and 0.9287. Similarly, the loss in training accuracy is 0.013, and the loss in prediction accuracy is 0.0713.

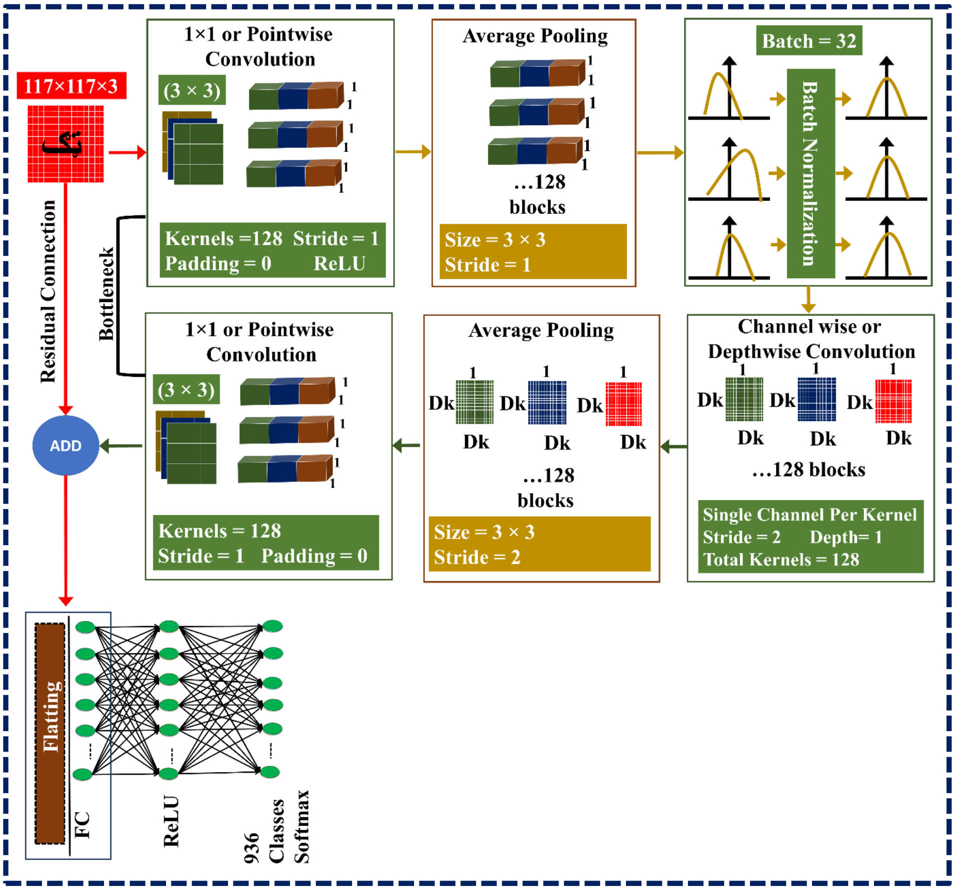

FIGURE 16. Model_2 based on MobileNetV2.

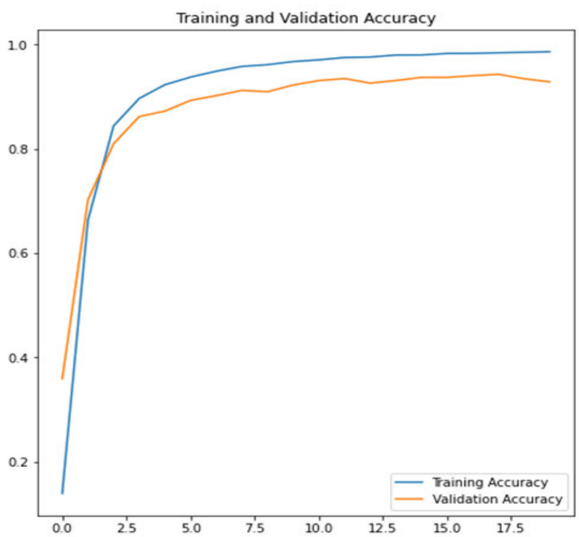

FIGURE 17. Model_2 training and prediction accuracy.

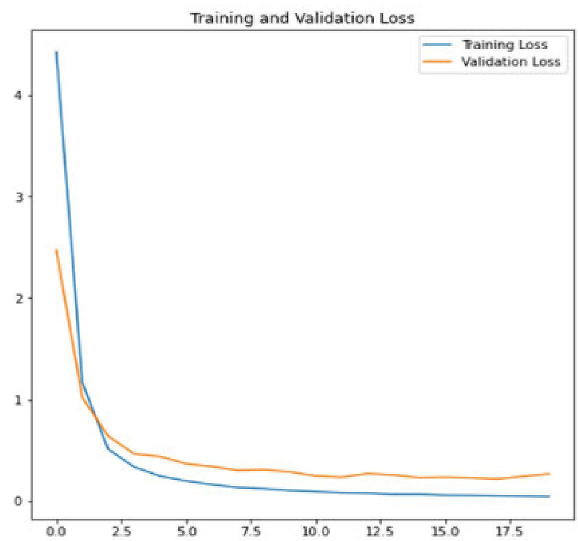

FIGURE 18. Model_2 training and prediction losses in accuracy.

The training and prediction accuracy is demonstrated in Fig. 17, and the losses in training and prediction are presented in Fig. 18.

Model_2 performed well in the training and prediction phases and achieved efficient results, as shown in Fig. 17. The losses demonstrated in Fig. 18 for the training and prediction phase are minimized compared to Model_1. Hence, Model_2 is better than Model_1 to adopt in commercial applications. The reason for good results by Model_2 is the inversion property of the dataset. The model dropped the black background pixels and used the maximum Pashto handwritten text trajectory pixels.

FIGURE 19. **Model_2 training and prediction accuracy on 15 epoch.**

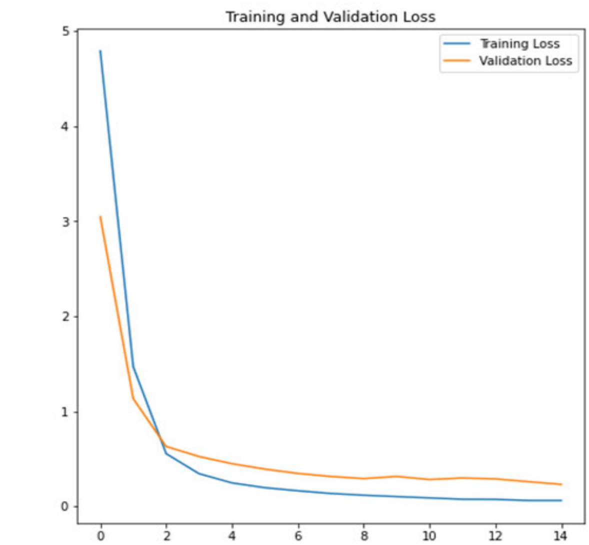

FIGURE 20. **Model_2 training and prediction losses on 15 epochs.**

Furthermore, the image size reduction to 117 × 117 × 3 helps the model converge fast. During this experiment, we realized that the number of epochs might be reduced to 15, making it more practical for low-resource devices. For 15 epochs, Model_2 becomes more accurate, fast, and efficient for low-resource devices. The Model_2 achieved a training accuracy of 0.9839 and a prediction accuracy of 0.9405, as shown in Fig. 19. Furthermore, this model on 15 epochs minimizes the loss in training and prediction accuracy to 0.0161 and 0.0595, respectively, as demonstrated in Fig. 20.

Table 3 compares the proposed technique with other deep learning-based lightweight geometric invariant Pashto handwritten word recognition techniques. The proposed technique is the only one that recognizes Pashto-isolated handwritten words with deep learning techniques. The deep learning techniques given in table 3 are not lightweight. The datasets used in these techniques are character-based or sentence-case instead of words based. In short, the proposed technique is different and efficient for Pashto handwritten words recognition, which has the property of geometric variation.

V. CONCLUSION

The cursive style of handwritten Pashto scripts and the connecting and non-connecting components of words make recognition systems difficult. The variety in transformation owing to differences in handwriting habits adds to the complexity. In the literature, several ways of word recognition highlight the method of using ascenders, descenders, and baselines while using traditional machine learning techniques. The existing deep learning-based techniques and datasets are either for Pashto handwritten characters or complete handwritten Pashto text line images. Furthermore, The existing deep learning techniques do not claim the lightweight property. This article proposes a lightweight, deep learning-based technique that recognizes the Pashto handwritten, transformed invariant words in an unconstrained environment for low to medium-resource devices. Two datasets of 936 classes, and each class have 100 transformed invariant samples. The first dataset has a white background, while the second one is the inversion of the first dataset with a black background. A light weighted MobileNetV2 has been tuned for handwritten Pashto words classification and recognition. The main reason for choosing the MobileNetv2 to hyper tuned for handwritten Pashto words is the idea of (MoI).

Furthermore, MobileNetV2 has inversion and residual properties, making it light-weighted. The proposed technique is comparatively analyzed with other available traditional machine learning-based and deep learning-based techniques in sections II and IV, respectively. Experiments show that the proposed model achieves a validation and testing accuracy of 0.9405 and a training accuracy of 0.9839 after fifteen epochs.

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