



Recognition of Handwritten Words from Digital Writing Pad Using MMU-SNet

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Abstract: In this paper, Modified Multi-scale Segmentation Network (MMU-SNet) method is proposed for Tamil text recognition. Handwritten texts from digital writing pad notes are used for text recognition. Handwritten words recognition for texts written from digital writing pad through text file conversion are challenging due to stylus pressure, writing on glass frictionless surfaces, and being less skilled in short writing, alphabet size, style, carved symbols, and orientation angle variations. Stylus pressure on the pad changes the words in the Tamil language alphabet because the Tamil alphabets have a smaller number of lines, angles, curves, and bends. The small change in dots, curves, and bends in the Tamil alphabet leads to error in recognition and changes the meaning of the words because of wrong alphabet conversion. However, handwritten English word recognition and conversion of text files from a digital writing pad are performed through various algorithms such as Support Vector Machine (SVM), Kohonen Neural Network (KNN), and Convolutional Neural Network (CNN) for offline and online alphabet recognition. The proposed algorithms are compared with above algorithms for Tamil word recognition. The proposed MMU-SNet method has achieved good accuracy in predicting text, about 96.8% compared to other traditional CNN algorithms.

Keywords: Digital handwritten writing pad; tamil text recognition; syllable; dialect

1 Introduction

According to Ethnologue statics, Tamil Language (TL) is a 5000-year-old language. TL is spoken in the state of Tamil Nadu, India and other countries such as Srilanka, Malaysia and Singapore. The Tamil Language is the oldest language of the Dravidian people. Tamil language alphabets have 12 vowels called Uyirezhuthu, 18 consonants called Meyyehuthu, and one unique character called Aythaezhuthu. The combinations of 12 vowels and 18 consonants lead to the uyirmeyyehuthu alphabet of 216 alphabets. The total TL alphabets are 247. TL has five consonants from the Sanskrit language, combined with Tamil vowels, and produces 60 alphabets; in total, TL has 307 alphabets [1]. Based on the centuries, TL alphabets are categorized into karosti ezhuthukal, Brahmi ezhuthukal, Vattu ezhuthukal,



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Grantha ezhuthukal and Tamil ezhuthukkal. The karosti ezhuthukal are written from right to left, which was first read by General Ventura in 1830. Brahmi ezhuthukal was used in India except in Tamil Nadu till the 6th century. Vattu ezhuthukal scripts are called disks because they are written in a circular pattern during Circa BC 500 to BC. Granth is a type of writing, referred to as Grantha Scripts, developed from the oldest form of Tamil script in Tamil Nadu after the 3rd century. Modern literary Tamil has continued since 1600. From the Brahmi script, the Tamil writing system developed. When printing was invented in the 16th century, the letter shapes underwent significant modification until finally settling. Although several letters with asymmetrical shapes were standardized throughout the modern era, the main change to the alphabet was the introduction of Grantha letters to express unassimilated Sanskrit words.

TL's writing style, alphabet, and slang vary from country to country, state to state, and region to region in India. Spoken TL is recognizable to all Tamil-speaking people, whereas recognizing the Tamil handwritten text from a digital writing pad is a complex and challenging task for computers and humans. A slight change in size and shape of the alphabet will change the meaning [2]. Visual interpretation of the TL alphabet is a challenging task and still a significant problem for computers to recognize the handwritten text of TL due to complex structures such as curves and loops in the alphabet. Especially when we write on a digital writing pad, the font and shape of the alphabet change for various reasons, and the meaning of the words is changed during OCR to text conversion using the software. The change in the alphabet is due to glass surfaces in the digital writing pads; writing on a frictionless surface glass shows a different alphabet after conversion from OCR to a text file, as shown in Fig. 1.

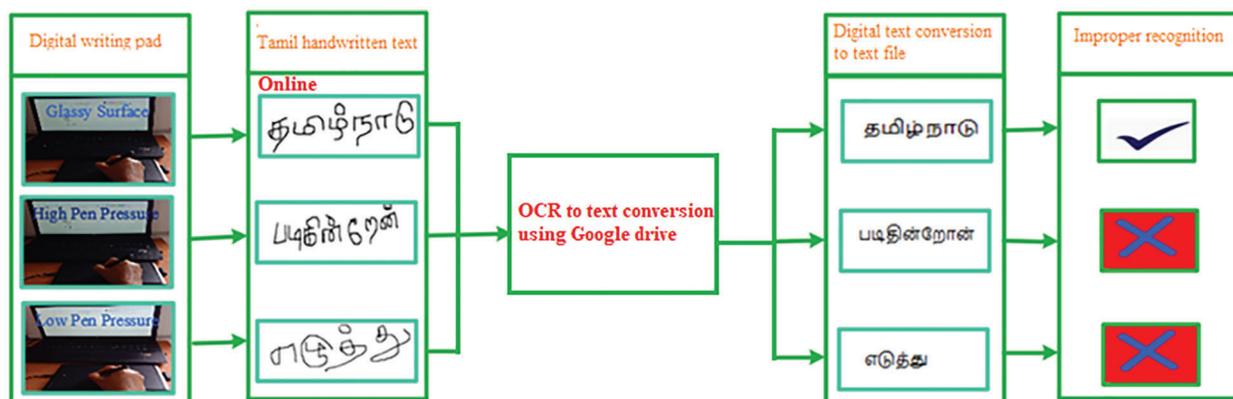


Figure 1: Tamil handwritten text from digital writing pad recognition through OCR google.doc

Moreover, the stylus has pressure sensitivity on the screen and within the stylus itself, which leads to changes in the curves in the alphabet. The handwritten notes into digital text conversion increased after COVID-19 pandemic during any conversion such as OCR to text or text to OCR. OCR is a technology that transforms text into a machine-readable form from handwritten, typed, scanned, or text contained inside images. Any image file containing text, a PDF file, a scanned document, a printed document, or a readable handwritten document can all be used with OCR to extract text. OCR can use OCR to eliminate manual data entry with digitized documents. OCR is also used for book scanning, where it turns raw images into a digital text format. The quality of OCR depends on the quality of the input image that is provided to it, and if there are any imperfections in an image, OCR will have a harder time extracting text from it.

Fig. 2 shows the Tamil handwritten text from digital writing pad recognition. The Tamil handwritten text from digital writing pad sentence in Fig. 2 நான் இன்று பள்ளி செல்கின்றேன் can be mispredicted

as நான் இன்று பள்ளி செல்கின்றேன் become meaningless. The real-time Tamil handwritten text from digital writing pad recognition problem can be overcome using the proposed MMU-SNet method.

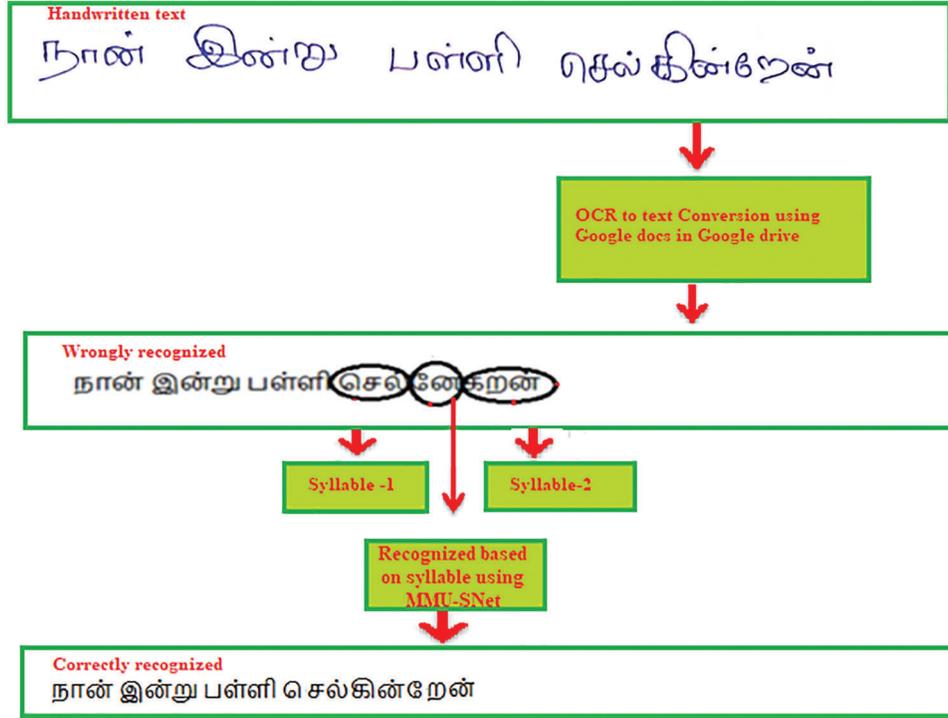


Figure 2: Tamil handwritten text from digital writing pad recognized using MMU-SNet

Automatic Recognition of Handwritten words from a digital writing pad and converting them into a text file is more challenging due to curvature and loops in text. The offline handwritten recognition is done on a skimmed image that contains the handwritten text for identification, which means the skimmed image's handwritten alphabet is translated to digital form and preserved in the computer. To solve the above problem, MMU-SNet is proposed, consisting of a Residual Module (RM) for constructing a backbone network (BN). The BN is separated into five stages and two times down sampling at each stage.

Contributions

- To recognize handwritten text using MMU-SNet algorithm based on semantic segmentation and upgraded Residual Module for better accuracy.
- To recognize digitized writings in Tamil language using dialect-based alphabet classification using MMU-SNet algorithm for regions such as Madurai, Tirunelveli, Coimbatore, and Thanjavur in Tamilnadu/India.
- To recognize digitized writings in Tamil language using syllable-based alphabet classification using MMU-SNet algorithm, CNN+SALA, AlexNet, and VGG19Net.
- To compare handwriting in the Tamil alphabet based on accuracy, precision, recall, and F1 score for dialect-based alphabet classification, syllable-based alphabet classification, and traditional alphabet classification.

2 Related Works

The recognition of handwritten Chinese text by segmentation is developed with the [3] integration of contextual data by guiding the network's feature extraction. A Recurrent Neural Network (RNN) is proposed for recognizing online handwritten Chinese text through different architectures such as weight vector and variance constraint [4]. Gurmukhi language in India has been recognized Gurmukhi language in India from an online handwritten alphabet based on preserved and marked stroke levels in the alphabet. RNN classifier achieved better accuracy in [5].

A Glyph Semanteme Fusion Embedding (GSFE) for Chinese text recognition is proposed. It consists of an encoder CNN-BiLSTM for extracting sequential features, and a Long Short Term Memory (LSTM) network is used as a decoder. The character level Glyph Semanteme Fusion Embedding (GSFE) and word level GSFE are used in the LSTM decoder for better prediction accuracy than the standard LSTM decoder [6]. Modified Artificial Neural Network (ANN) is used in Tamil handwritten character recognition, which consists of Elephant Herding Optimization (EHO) for the optimization of weights in ANN [7].

Handwritten English text recognition on historical documents using CRNN improves recognition accuracy. The Fully Convolutional network (FCN) is proposed for unconstrained English Text recognition [8]. The performance in classifying depth-wise separable convolutions is a key computational component. PUNet is an efficient deep learning architecture for English hand-written word spotting. In PUNet is developed with U-Net and pyramidal histogram [9].

Multi-Dimensional Long Short Term Memory (MDLSTM) is used in Arabic offline handwriting recognition. The MDLSTM is used for many recurring connections. There are spatiotemporal dimensions in the data. These connections are used to create flexible internal context representation [10]. A CNN-based model is proposed for Tamil offline handwritten recognition; the individual characters are segregated from the text then the segregated character is given to the trained CNN model and predict the character. Hyperparameter tuning is used in the model and achieves reasonable accuracy [11]. Fast writer adaption with the Style Extractor Network (SEN) is proposed for Chinese handwritten text recognition. SEN extracts personalized writer information [12].

Besides this, [Table 1](#) tabulates the dataset, methods, and writing devices used for handwritten recognition in various languages.

Table 1: Represents the various languages, datasets, and methods used for handwritten recognition

References	Year	Language	Dataset	Method writing devices
[13]	2019	English German	ICDAR and ICFHR	CRNN Paper and pen
[14]	2021	Chinese	CASIA and ICDAR	FCNN Paper and Pen
[15]	2021	Gurmukhi	Dataset created by Singh et al. (2016), Singh and Sharma (2019)	Deep Pen tablets CNN
[16]	2021	Arabic	Hijja and AHCD	CNN Paper and Pen
Proposed work MMU-SNet	2022	Tamil	Manually collected DWP-Tamil dataset	MMU-SNet Digital writing Pad

3 Proposed MMU-SNet Method

Fig. 3 shows the block diagram of Tamil handwritten text recognition and classification from digital writing pad recognition using MMU-SNet. The text images are obtained from offline, such as text written on paper and pen, online, and note-taking for recognition of Tamil text. DWP-Handwriting (DWP-H) database contains handwritten Tamil characters. DWP-H dataset was collected using Wacom CTL-672/K0-CX Graphic Tablet used for online and offline writer identification and verification experiments. Text datasets were collected from ambient lighting conditions and pressure base stylus writing on the digital pad. A total of 151 writers' contributions are in tiff format, obtained from different age groups such as children, adults, old males, and females. Samples per class 5, a few contributed as many as ten, and the number of samples per class is 150 samples with the character of size 92×133 . The writers are from different demographics of regions such as Chennai, Madurai, and trichy in Tamilnadu. The writing style of different writers from different demographics shows variation in stylus pressure and character. The DWP-H Database is available in the following Google drive link. <https://drive.google.com/drive/folders/1nzJL4puQ4Ly9fpi2jHxteDgPjwCUupqx?usp=sharing>. Fig. 4 shows the model built-in backbone network (BN) in an encoder with the upgraded residual basic module. There are five stages in the backbone network, and two times downsampling can be performed in each stage. A basic Residual Module (RM) in each stage is 2. The added non-local attention module after the backbone network's last module captures spatial features and long-term context information and avoids increasing parameters and calculations.

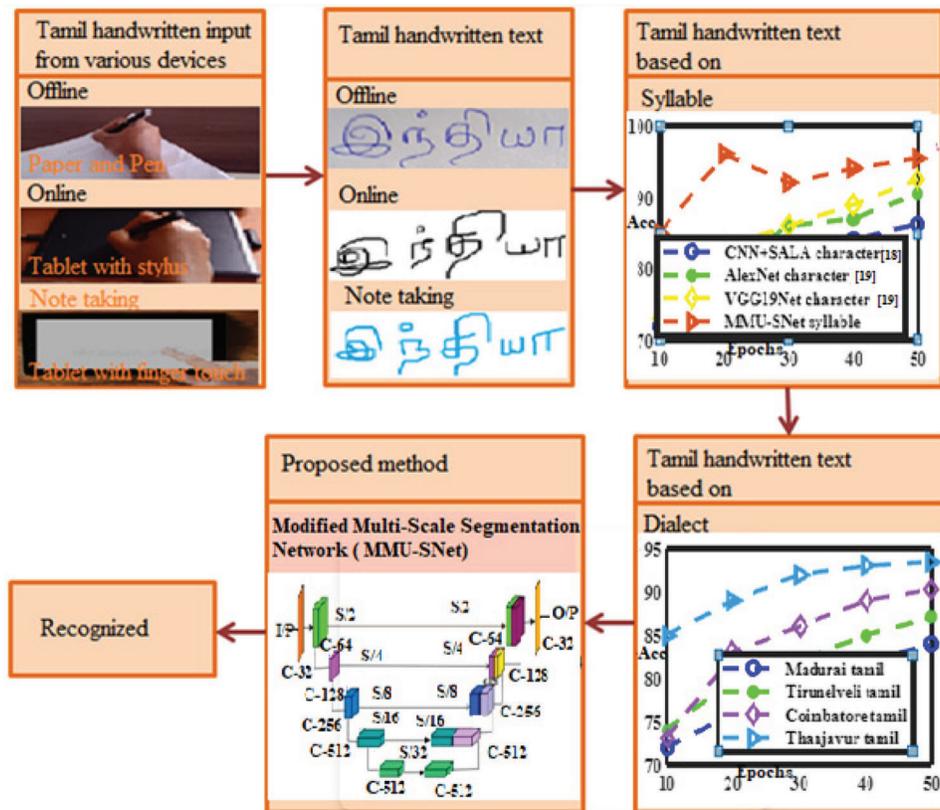


Figure 3: Tamil handwritten text from digital writing pad recognition using MMU-SNet

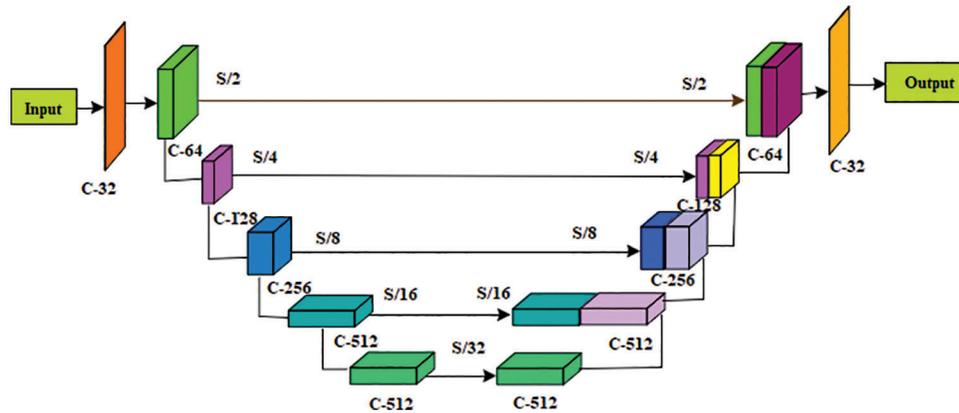


Figure 4: Modified multi-scale segmentation network (MMU-SNet) architecture

A U-shaped skip connection structure similar to U-network is used to recover more detailed information. Finally, the Up-sampling and classification module restore the activation map to the size of the input image. The upgraded RM is used in Multi-Scale (MS). The RM is shown in Fig. 5; the two modules with slight variation are designed to carry out down sampling.

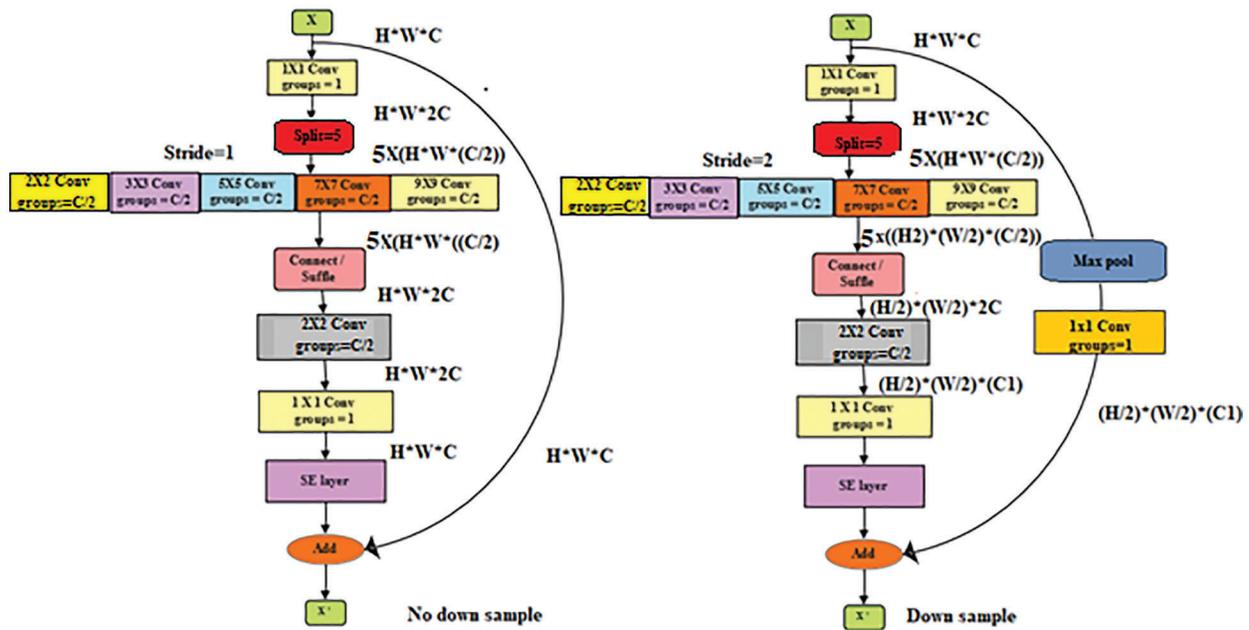


Figure 5: Multi-scale residual module

The various initial residual networks carry out the procedure of reducing the dimensionality first and then expanding the channel in our proposed MMU-SNet system, first expanding and after reducing the dimensionality of the channel in [17]. Precisely, to raise the channel dimension of the input feature two times, use 1×1 convolutions, and based on the channel dimension, the activation map is divided into five small activation maps. Then the depth-wise separable convolution with the convolution filter size of $[2 \times 2, 3 \times 3, 5 \times 5, 7 \times 7, 9 \times 9]$ is used to achieve the convolution operation on the five activation maps and then attach the five activation maps into a new large activation map in the channel dimension.

Subsequently, apply 2×2 group convolutions to merge multi-scale features and then utilize 1×1 convolutions to decrease the channel dimension. In the meantime, a channel attention module of the Squeeze Excitation (SE) layer is added after this step. The SE layer is used for feature recalibration. The core of SE is compression, squeeze, and excitation. After the convolution operation has obtained the features with the multi-channels and then recalibrates the weight of each feature channel using an SE layer.

At last, adding the residual connection of input features is carried out. It is essential to observe that the max pool and 1×1 convolution operations are achieved by downsampling the input features previous residual connection. Simultaneously, the BN layer is added later to each convolution layer. Moreover, to the five convolution layer, which extracts multi-scale features, the RELU activation layer is added to each convolution layer.

4 Model Implementation

The PyTorch-1.5 framework is used to build our network. The models are trained o with a memory capacity of 24 GB, mini-batch practice with Stochastic Gradient Descent (SGD) as the optimizer to train the network, with batch size set to 64 and the learning rate is 0.0001. The cross-entropy loss function is used in training. The image was resized to $50 * 50$. Finally, arbitrarily shamble the training samples with 50 epochs of training.

5 Results and Discussion

This part begins with a brief overview of the test bases and a summary of the performance metrics employed for the assessment. Then, mathematical results and a helpful comparison are delivered. We conclude by giving a brief analysis of our approach.

5.1 Evaluation Metrics

Four statistical measures are used to evaluate the MMU-SNet classifier's effectiveness: Accuracy, precision, recall, and F1 score. The metrics are calculated mathematically in Eqs. (1)–(4), where the True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Table 2 show the performance analysis of classifiers with accuracy, precision, recall, and F1 score.

Table 2: Performance analysis of classifiers with accuracy, precision, recall, and F1 score

Classifiers	Accuracy	Precision	Recall	F1
CNN + SALA [18]	86.3%	88.4%	94.3%	91.2%
AlexNet [19]	90.5%	92.6%	98.5%	95.4%
VGG19Net [19]	92.5%	93.5%	96.7%	95.0%
MMU-SNet	96.8%	99.3%	97.4%	98.3%

The accuracy metric commonly defines how the model completes across all classes. Accuracy is calculated as the ratio of correct predictions to the total number of predictions.

$$\text{Accuracy (A)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (1)$$

The P is calculated as the ratio between the numbers of positive samples correctly classified to the total number of samples classified as positive. The P measures the model's accuracy in classifying a sample as positive.

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

The R is calculated by dividing the total number of positive samples by the proportion of positive samples correctly identified as positive. The R evaluates a model's capacity to identify positive samples. More positive samples are found when R is higher.

$$\text{Recall (R)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

The F1 score is the weighted average of P and R. This F1 score takes both false positives and false negatives into account.

$$\text{F1} = 2 * \frac{\text{P} * \text{R}}{\text{P} + \text{R}} \quad (4)$$

Figs. 6 to 9 shows the accuracy, precision, recall, and F1 score of the proposed MMU-SNet with the existing classifier, the Convolutional Neural Network, and Self Adaptive Lion algorithm (CNN+SALA) never encoding the position and orientation of the alphabet into their predictions. CNN makes predictions of an image by determining whether there are edges, endpoints, and corners, then the image is classified appropriately. The AlexNet model comprises five consecutively connected Conv layers of reducing filter size tailed by three fully linked layers. The main characteristic of AlexNet is the fast downsampling of the in-between representations using stridden conv and max pooling layers. The final convolutional map is reshaped into a vector and treated as an input to a sequence of two fully linked layers of 4096 units in size. The depth of the AlexNet model is significantly less; it performs less in learning features from image sets and consumes more time with fewer accuracy results. The VGG19Net model uses a sequence of conv layers with small filter sizes, such as 3×3 and has more profound conv architecture than AlexNet. Except for the final conv layer, which is followed by two fully linked layers, each series of conv layers is followed by a max pooling layer. The VGG19Net is slower and experiences a vanishing gradient problem. A proposed semantic segmentation network for handwritten words with less computation and memory. The first modifies the U-type skip-connection structure of the U-Net network to recover more comprehensive information in the decoder. The second step is to boost the residual network's RM and expands the network's receptive field size and multi-scale features. Moreover, it utilizes the attention mechanism, gathers long-term context information, and strengthens the network's capacity for representation.

5.2 Dialect

A similar word that can speak differently in various languages according to the user is called dialect. The speaker's social and geographic background determines the dialect. The language may vary from one region to another. In Tamilnadu, there are numerous dialects according to the area where there are spoken. Tamil languages as dialects in Tamil Nadu are in various cities such as Madurai Tamil, Tirunelveli Tamil, Coimbatore, and Thanjavur. Tamil dialects are distinguished from each other by different phonological changes and sound shifts in developing from old Tamil. For example, the word for "here," inku (இங்கு) in the dialect of Coimbatore, inga (இங்க) in the dialect of Thanjavur and old Tamil's inkan (இங்கண்) is the source of inkane (இங்கனே) in the dialect of Tirunelveli, old Tamil inkittu is the source of inkuttu (இங்குட்டு) in the dialect of Madurai. Table 3 shows the performance analysis of the classifier with accuracy, precision, recall, and F1 score based on the dialect.

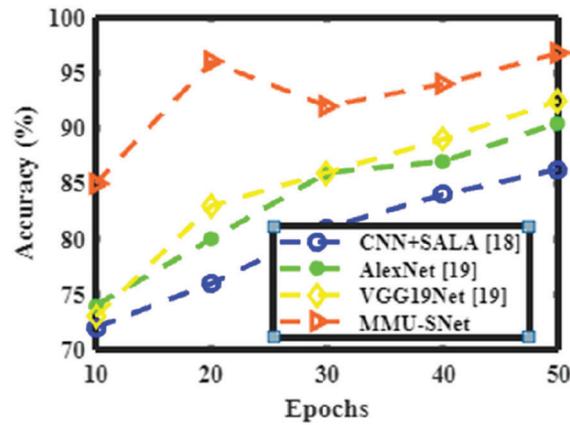


Figure 6: Performance analysis of various methods in terms of accuracy

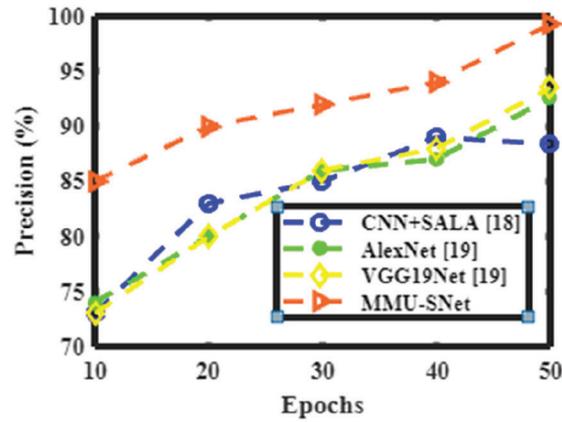


Figure 7: Performance analysis of various methods in terms of precision

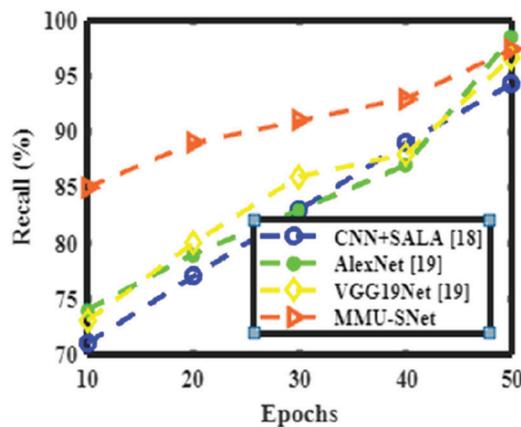


Figure 8: Performance analysis of various methods in terms of recall

Figs. 10 to 13 shows the accuracy, precision, recall, and F1 score of dialects spoken in Madurai Tamil, Tirunelveli Tamil, Coimbatore Tamil, and Thanjavur Tamil.

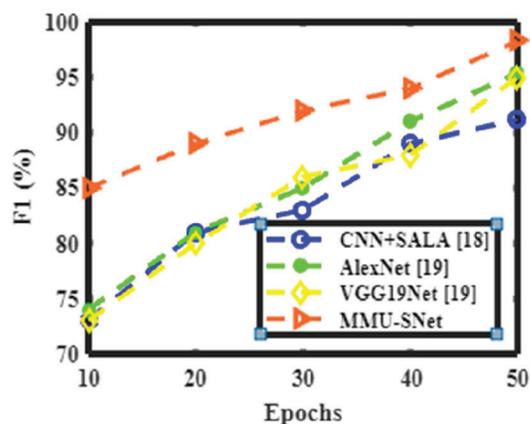


Figure 9: Performance analysis of various methods in terms of F1

Table 3: Performance analysis of classifier with accuracy, precision, recall, and F1 score based on the dialect

MMU-SNet	Accuracy	Precision	Recall	F1
Madurai Tamil	83.9%	96.1%	86.2%	90.9%
Tirunelveli Tamil	87.1%	96.3%	89.6%	92.8%
Coimbatore Tamil	90.3%	96.4%	93.2%	94.8%
Thanjavur Tamil	93.5%	98.6%	94.7%	96.6%

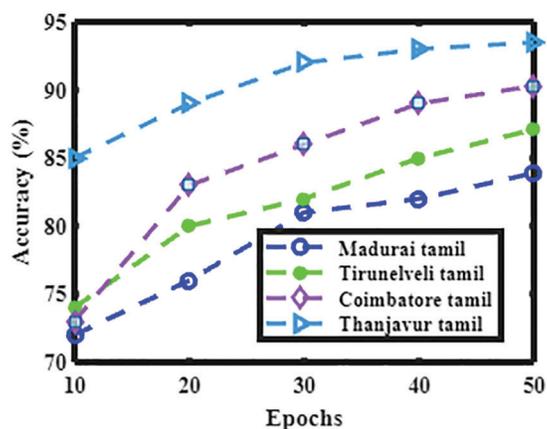


Figure 10: Performance analysis of the present method with various Tamil dialects in terms of accuracy

5.3 Syllable

Syllabication is dividing a word into smaller parts known as syllables, a single unbroken sound of a spoken or a written word. A word or a part of a word contains a vowel sound, the first step in syllables to identify the vowels in a word. The number of vowel sounds in a word equals the number of syllables. Identify the vowels and break the word according to the vowel sounds. Table 4 shows the Performance analysis of classifiers with accuracy, precision, recall, and F1 score based on a syllable.

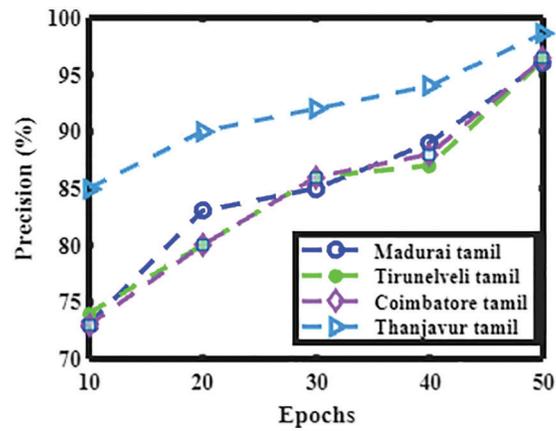


Figure 11: Performance analysis of the present method with various Tamil dialects in terms of precision

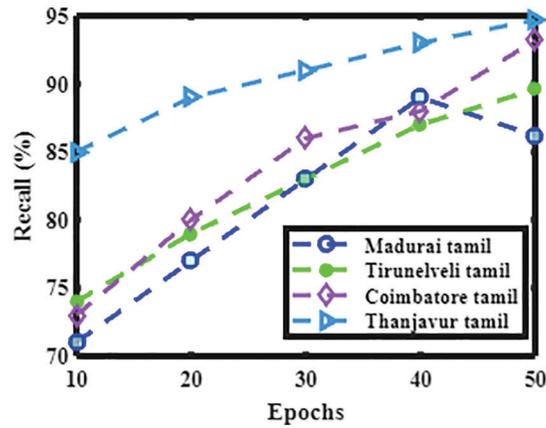


Figure 12: Performance analysis of the present method with various Tamil dialects in terms of recall

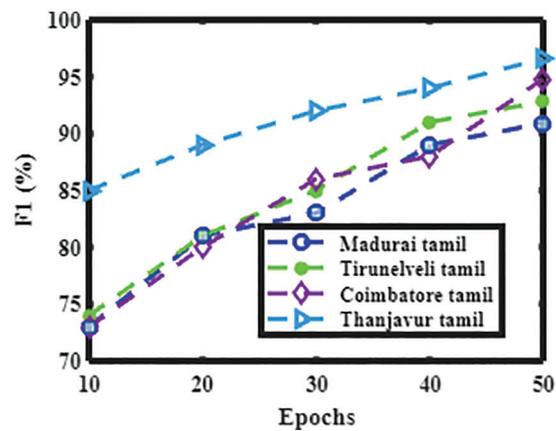
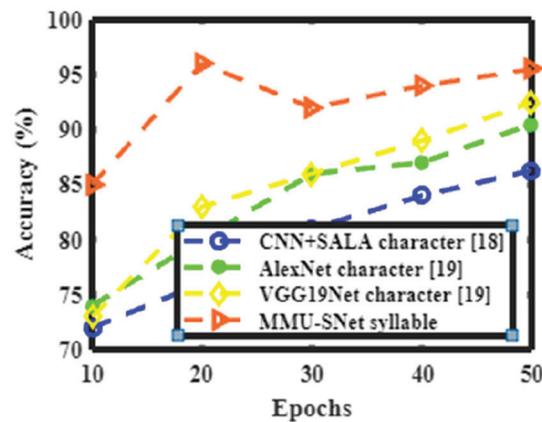
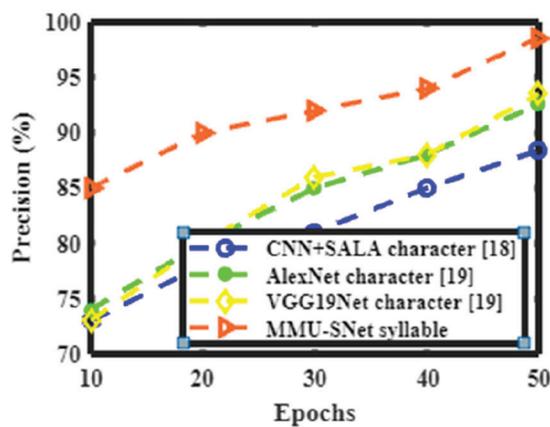


Figure 13: Performance analysis of the present method with various Tamil dialects in terms of F1

Table 4: Performance analysis of classifiers with accuracy, precision, recall, and F1 score based on syllable

Classifiers	Accuracy	Precision	Recall	F1
CNN+SALA (character) [18]	86.3%	88.4%	94.3%	91.2%
AlexNet (character) [19]	90.5%	92.6%	98.5%	95.4%
VGG19Net (character) [19]	92.5%	93.5%	96.7%	95.0%
MMU-SNet (syllable)	95.5%	98.6%	96.7%	97.6%

Figs. 14 to 17 shows the accuracy, precision, recall, and F1 score of the proposed MMU-SNet with classifiers CNN+SALA, AlexNet, and VGG19Net. The proposed MMU-SNet system achieved high accuracy, precision, recall, and F1 score based on a syllable.

**Figure 14:** Performance analysis of the present method with the various method in terms of accuracy**Figure 15:** Performance analysis of the present method with the various method in terms of precision

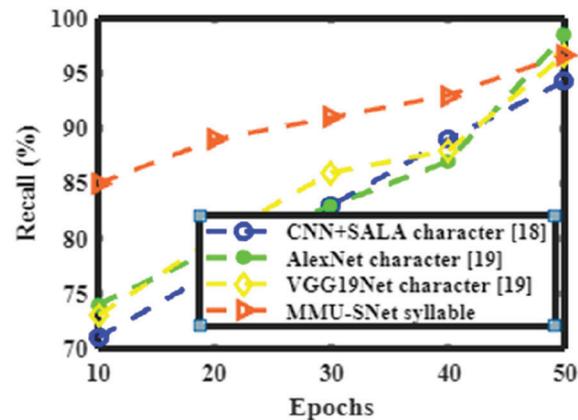


Figure 16: Performance analysis of the present method with the various method in terms of recall

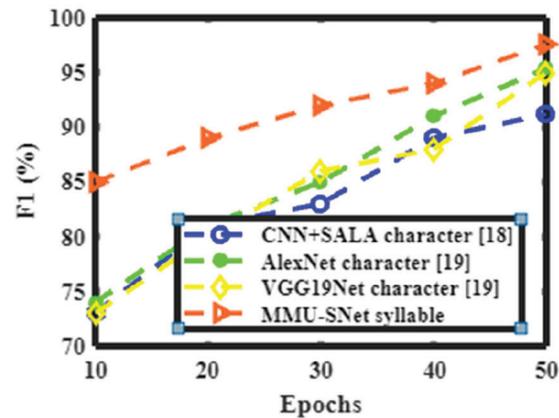


Figure 17: Performance analysis of the present method with the various method in terms of F1

6 Conclusion

The Modified Multi-scale Segmentation Network (MMU-SNet) is proposed for digital writing pad-based handwritten text detection and classification. Handwritten character changes Tamil words due to stylus pressure, writing on a frictionless glass surface, and less skilled in short writing, alphabet size, style, carved symbols, and orientation angle variations solved through the proposed MMU-SNet. The proposed MMU-SNet method compared with various neural network architectures such as CNN+SALA, AlexNet, and VGG19Net. The proposed MMU-SNet method has achieved good accuracy in predicting text, about 96.8% compared to other traditional CNN algorithms. The proposed MMU-SNet applies to Tamil handwritten text from digital writing pad recognition. The semantic segmentation provides pixelwise recognition, which is convenient for handling complex Tamil handwritten text from a digital writing pad. For example, the alphabet overlaps with other alphabets and spaces in between alphabets. Generally, semantic segmentation is used to label each pixel of an image with a corresponding class to which it belongs. The proposed MMU-SNet performs better than traditional architecture.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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