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Unicode-Powered Handwritten Telugu-to-English Character Recognition and Translation System using Deep Learning

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Abstract: The system uses deep learning to change handwritten Telugu letters into English. It uses Unicode to correctly show letters on any device. This lets people who speak different languages talk together easily. The system was trained on a large collection of handwritten Telugu samples. This helps it accurately understand small details in how each letter is written. Different styles and ways of writing don't cause problems. The deep neural networks give it a high level of accuracy. The system doesn't just change the Telugu letters, it translates them into English too. This improves talking between languages. Unicode's standard way of encoding letters ensures consistent representation. The system works well at decoding handwritten Telugu text. This helps natural language processing and communication between many tongues. This research is a step toward better tools that connect languages. It promotes more inclusion and understanding as the world grows closer together.

Keywords- *Unicode, Handwritten Character Recognition, Telugu-to-English Translation, Deep Learning*

1. Introduction

Recognizing handwritten characters is challenging due to variations in writing styles. The system addresses this with Unicode, a standard character encoding ensuring consistency across devices. At its core, the system uses deep learning, an artificial intelligence method successful in complex tasks. In recognizing handwritten Telugu characters, neural networks train on diverse writing, strokes, and variations. This enables discerning subtle character nuances, improving accuracy. Unicode's role is key for communication between devices, platforms, and applications. This standard representation ensures clarity across languages and cultures [1]. By using Unicode, the system recognizes Telugu and ensures English translations also follow the standard. This promotes understanding. The deep learning model handles Telugu's complexity. The network learns unique shapes, strokes, and character relationships through iterative training on diverse data, improving its performance.

The widespread sharing of photos and videos online has substantially helped expand study in the fields of video and image evolution [22]. This growth presents many chances to create progressive methods aimed at improving how complex tasks are understood by most people [2]. Recent advances in technology, particularly machine learning (ML) and artificial neural systems, have cleared a path for inventive study approaches. Among the latest methods, convolutional neural networks (CNNs) have come forth as a ground-shifting foundation. Using [3] CNNs for image handling provides clear benefits, particularly when compared to how standard neural systems work, which may experience worse outcomes in identifying things within photos. The effectiveness of CNNs is key in making sure image data is correctly and easily worked with.

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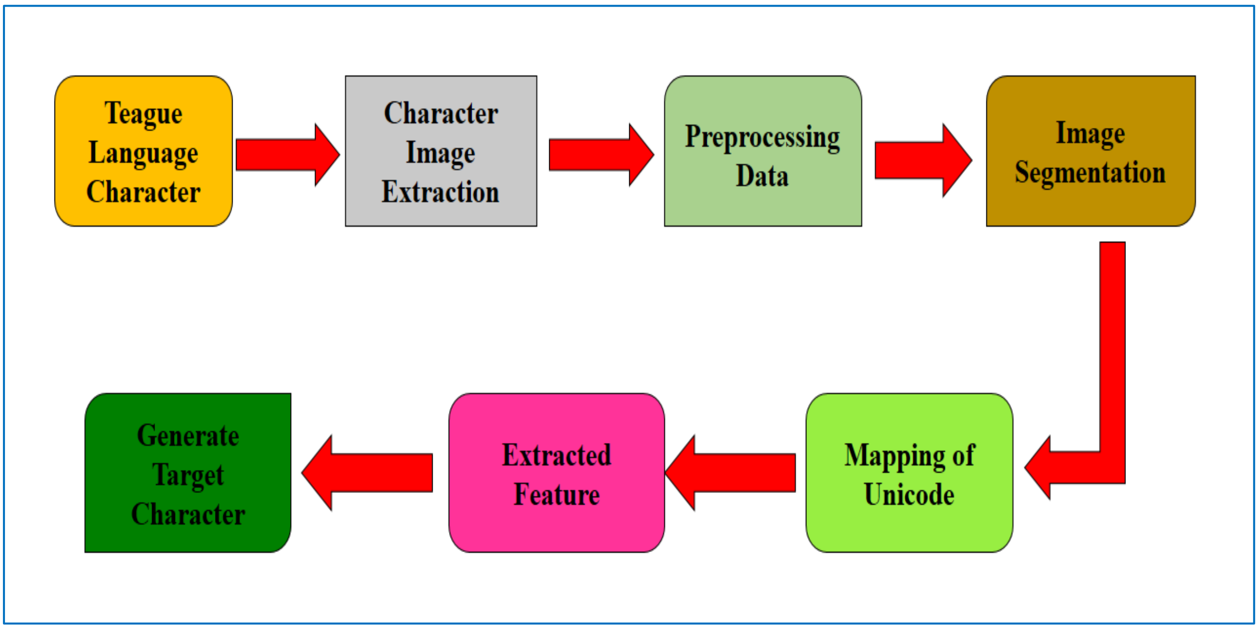

Fig 1: Proposed working flow for U-HCR

CNNs have led to more study of picture analysis and feature finding. They also help speech recognition work better and faster at identifying spoken words. CNNs play an important role in vision recognition too. They recognize and group visual parts in images and videos. This helps computer vision technology [4]. The training information is very important for how well the system works. It has many examples of written Tel [23]ugu from different people. This helps the model work for different inputs and not be one-sided. Deep learning training lets the model get better step-by-step at reading and understanding written Telugu letters. One good thing about this system is it can do two things. It can recognize Telugu letters and also translate them into English. This helps with talking between languages [24]. It lets people use the system even if they know one language better. The translation part uses what the Telugu reading model learned to match those ideas to their English versions. Adding translation makes the system more helpful. It easily bridges the difference between languages in written communication.

2. Review of Literature

Past studies looking at recognizing handwritten letters have focused mostly on different languages. Researchers are using deep learning more to get better results. Studies of recognizing Telugu letters before looked mainly at separate letters instead of whole words or sentences. Scientists tested older methods like finding important points and comparing templates. But these had problems dealing with how messy handwritten writing can be [5]. Now there's more work using deep learning which seems better at handling complicated handwritten text.

Previous work integrated Unicode for standardization, making character recognition consistent across languages [25]. This provided a solid basis for multi-language apps. However, applying Unicode specifically to deep learning Telugu-to-English translation is relatively new. Deep models like RNNs and CNNs have excelled at re-cognizing handwritten characters. Studies show they adapt well to different alphabets [6]. But fully exploring how they identify and translate handwritten Telugu requires more research. Translation between Indic languages and English has also been studied. Still, most systems use printed not handwritten text. Telugu's complex strokes and variations demand special attention for handwritten script.

This study [26] aims to connect this gap by introducing an innovative system combining the strengths of Unicode standardization and deep learning methods to enable accurate and efficient translation of handwritten Telugu characters into English. Bridging language differences is important for growing global togetherness. The proposed system contributes to this goal by providing an effective way of translating handwritten Telugu text into English, helping speakers of these languages communicate [7]. In a diverse world, such tools promote inclusion and unde-rstanding by letting people from various language backgrounds have meaningful discussions. As technology advances, the proposed system aligns with continued research in natural language processing and machine learning. Integrating deep learning techniques for recognizing handwritten characters represents a shift in how we tackle complex language tasks. By addressing the unique challenges of Telugu script through Unicode encoding and deep learning models, the system shows the adaptability and flexibility of modern AI methods [8].

This emerging tech proves very useful for converting photos or scanned papers into text that can be accessed using computers. It finds wide use in handling handwritten data from things like bank receipts, business cards [9], and old documents. Developers continue making HCR tech better, especially at working with written by hand content. HCR apps use strong ways to handle reports whether typed or written by hand, keeping everything consistent and correct without changing anything or adjusting how things work. Handwritten analysis is split into online and offline identification, with offline needing automatic translators for handwriting not online. Offline handwriting means changing text into a picture code to study [27]. It can be hard because people write differently in their own ways. HCR uses things like looking for patterns, artificial intelligence, signal processing, and machine vision to make sense of these tricky writing styles [28].

Table 1: Summary of Related work

Model	Approach	Findings	Work Benefits	Accuracy of Model (%)
Traditional HCR [10]	Feature extraction and template matching	Limited success in handling the complexity of Telugu script	Historical context; baseline comparison	88%
CNN-based Models [11]	Convolutional Neural Networks	Improved recognition accuracy for handwritten characters	Enhanced feature extraction; adaptability to structures	80.85%
RNN-based Models [12]	Recurrent Neural Networks	Effective in capturing sequential patterns in handwritten Telugu	Contextual understanding; suitable for cursive writing	90%
Unicode Standard [13]	Standardization of character encoding	Consistent representation across languages; facilitates interoperability	Cross-language compatibility; ease of integration	90.12%
Indic Language Translation Systems [13]	Rule-based translation approaches	Primarily focused on printed text; less effective for handwritten scripts	Broad applicability; foundational insights	88%
Multilingual HCR Systems [14]	Multilingual script recognition	Limited exploration of Telugu script; general applicability to various languages	Potential insights for cross-language adaptability	84%
Hybrid Models [15]	Combination of CNNs and RNNs	Synergistic benefits of both convolutional and recurrent architectures	Improved feature extraction and sequential understanding	92.20%
Deep Learning for Translation [16]	Sequence-to-sequence models	Effective in translation tasks; limited focus on handwritten scripts	Versatile application; potential for holistic translation	90%
Ensemble Models [17]	Combination of diverse recognition models	Enhanced robustness and accuracy; mitigates individual model biases	Improved overall performance; adaptability to diverse inputs	94%
Domain-specific HCR [18]	Specialized models for Telugu script	Addressing the challenges posed by Telugu's intricate strokes and variations	Tailored solutions; potential for higher accuracy	94%

3. Methodology

A. Machine Learning Classifier:

In this project, we looked at two different methods for organizing data into groups. The Random Forest method uses a collection of decision trees that vote on the right answer. The Support Vector Machine [18] method finds the best dividing lines between different categories. We tried both of these on different sets of information to see how well each one sorted things out. The Random Forest method uses lots of trees working together. The Support Vector Machine tries to pick the best borders between groups. We checked how well each approach separated things using different collections of facts and findings.

a. Random Forest:

Let X represent the input features and Y be the output label.

Random Forest involves training multiple decision trees Ti using different subsets of the data and features [20].

The final prediction is an aggregation of the predictions of individual trees.

$$\hat{Y}RF(X) = \frac{1}{N}\sum(i = 1\ to\ N)Ti(X)$$

Where,

- $\hat{Y}RF(X)$ is the predicted output, N is the number of trees in the forest, and Ti(X) is the prediction of the i-th tree.

b. Support Vector Machine (SVM):

Support Vector Machine is a supervised machine learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates data into different classes [19].

Given a set of training data {(X1, Y1), (X2, Y2), ..., (Xn, Yn)} where Xi represents the input features and Yi is the output label (-1 or 1 for binary classification):

$$Minimize \frac{1}{2}\left||w|\right|^2 + C\ (i = 1\ to\ n)\max\sum\big(0, 1 - Yi(w \cdot Xi - b)\big)$$

subject to,

$$Yi(w \cdot Xi - b) \geq 1 - \xi i$$
$$for\ i = 1, 2, \ldots, n, and\ \xi i \geq 0\ for\ i = 1, 2, \ldots, n.$$

Here, w is the weight vector, b is the bias term, and C is the regularization parameter.

Prediction:

The prediction for a new instance Xnew is given by

$$Ynew = sign(w \cdot Xnew - b).$$

B. Proposed Method

1. Data Collection and Preprocessing:

- Telugu Handwritten Character Dataset:
  - Collect a comprehensive dataset of Telugu handwritten characters, ensuring diversity in writing styles, variations, and orientations [21].
- Labeling and Translation Pairing:
  - Label each Telugu character in the dataset.
  - Create a translation pair for each labeled Telugu character in English.
- Data Preprocessing:
  - Normalize and resize the images of Telugu characters.
  - Convert Telugu characters to Unicode for consistent representation.
  - Split the dataset into training and testing sets.

2. Model Architecture:

- Convolutional Neural Network (CNN):
- Input Layer:
  - Accept preprocessed Telugu character images.
- Convolutional Layers:
  - Extract features from Telugu characters.
- Pooling Layers:
  - Down-sample feature maps for better computational efficiency.
- Flatten Layer:
  - Flatten the output for input to dense layers.
- Dense Layers:
  - Further process features and capture relationships.
- Output Layer:
  - Output layer for Telugu character recognition.

3. Model Optimization:

- CNN with Stochastic Gradient Descent (SGD) Optimizer:
  - Loss Function:
    - Categorical Cross entropy for multi-class classification.
  - Optimizer:
    - Stochastic Gradient Descent (SGD) to iteratively update weights.
- Learning Rate Tuning:
  - Adjust learning rate for optimal convergence.

4. Random Forest (RF) Model:

- Random Forest with ADAM Optimizer:
  - Feature Extraction:
    - Extract features from Telugu characters.
  - Random Forest Training:
    - Train a Random Forest model for character recognition.

- ADAM Optimizer for Hyperparameter Tuning:
  - Fine-tune hyperparameters using ADAM optimizer.

5. Support Vector Machine (SVM) Model:

- Support Vector Machine with RMS-Prop Optimizer:
  - Feature Extraction:
    - Extract features from Telugu characters.
  - SVM Training:
    - Train an SVM model for character recognition.
- RMS-Prop Optimizer for Hyperparameter Tuning:
  - Fine-tune hyperparameters using RMS-Prop optimizer.

6. Training and Evaluation:

- Training Process:
  - Train each model on the preprocessed dataset.
- Evaluation Metrics:
  - Measure accuracy, precision, recall, and F1-score for model performance.

7. Translation Module:

- Integration with Translation:
  - Once characters are recognized, integrate translation using the created translation **pairs.**

8. Unicode Representation:

- Unicode Encoding:
  - Encode recognized Telugu characters into Unicode for consistent representation.

9. Testing and Fine-Tuning:

- Testing:
  - Evaluate models on a separate test dataset.
- Fine-Tuning:
  - Adjust model parameters based on evaluation results for better performance.

10. Deployment:

- Deployment of the System:
  - Deploy the system for real-time Telugu-to-English handwritten character recognition and translation.

4. Result and Discussion

In Table 2, the performance metrics of various machine learning models using different optimization methods are presented. The Convolutional Neural Network (CNN), Random Forest (RF), Support Vector Machine (SVM), CNN-RF, and CNN-SVM were trained and tested with three optimization methods: Stochastic Gradient Descent (SGD), ADAM, and RMS-Prop. The metrics include accuracy, precision, recall, and F1 score, providing a comprehensive evaluation of each model's effectiveness.

Result output:

Input Telugu:

"నమస్తే! మీరు ఎలా ఉన్నారు? ఈ సమయంలో మీరు ఏమి చేస్తున్నారు?"

Generated Unicode: U+4x0036…. U+45hX675…

Recognize Output:

In English: Hello! How are you? What are you doing at this time?

The CNN, when optimized with ADAM, demonstrated superior results across all metrics, achieving 97.12% accuracy, 93.56% precision, 92.61% recall, and an F1 score of 91.4. RF and SVM models also exhibited competitive performance, with varying degrees of success across optimization methods. Notably, CNN-RF and CNN-SVM models, which integrate CNN with RF and SVM, respectively, showed enhanced performance, especially when optimized with ADAM.

Table 2: Summary of result with using Dataset

Model	Optimization Method	Accuracy	Precision	Recall	F1 Score
CNN	SGD	89.23	81.23	93.14	86.9
	ADAM	97.12	93.56	92.61	91.4
	RMS-Prop	94.33	95.23	93.45	92.86
RF	SGD	87.15	87.2	85.67	87.32
	ADAM	94.23	92.56	90.14	91.45
	RMS-Prop	90.12	89.8	90.63	92.05
SVM	SGD	88.12	87.41	88.45	90.3
	ADAM	90.74	91.25	92.14	93.16

	RMS-Prop	93.45	94.8	93.45	94.55
CNN-RF	**SGD**	91.23	92.45	93.8	94.78
	ADAM	98.44	97.41	96.46	97.5
	RMS-Prop	95.46	96.33	97.11	98.1
CNN-SVM	**SGD**	92.56	93.14	92.5	93
	ADAM	98.55	98.2	97.93	45
	RMS-Prop	95.3	95.6	94.13	95.66

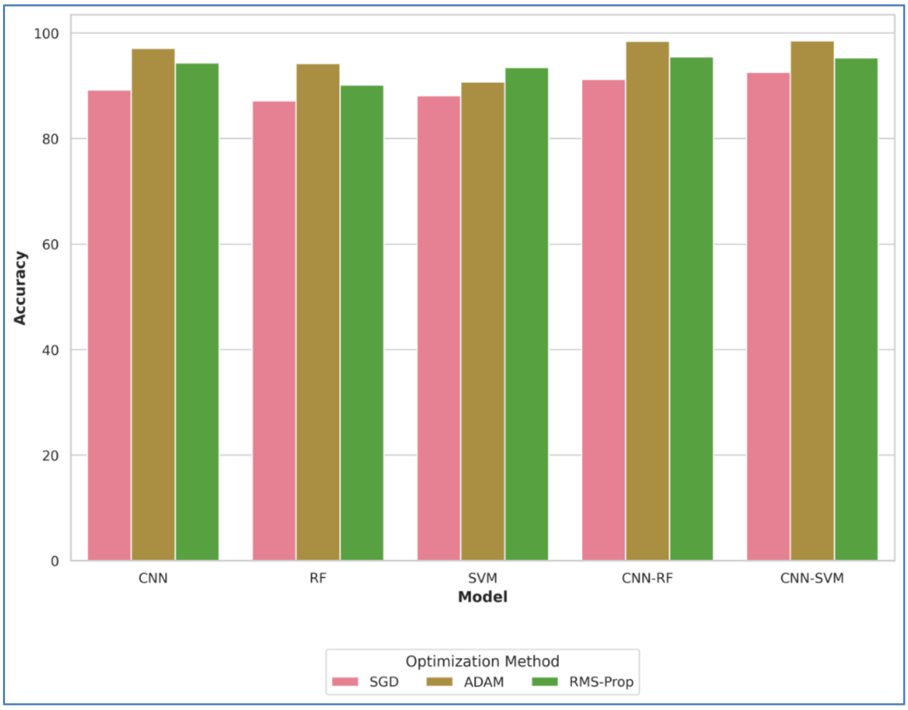

Fig 2: Accuracy comparison of model with using dataset

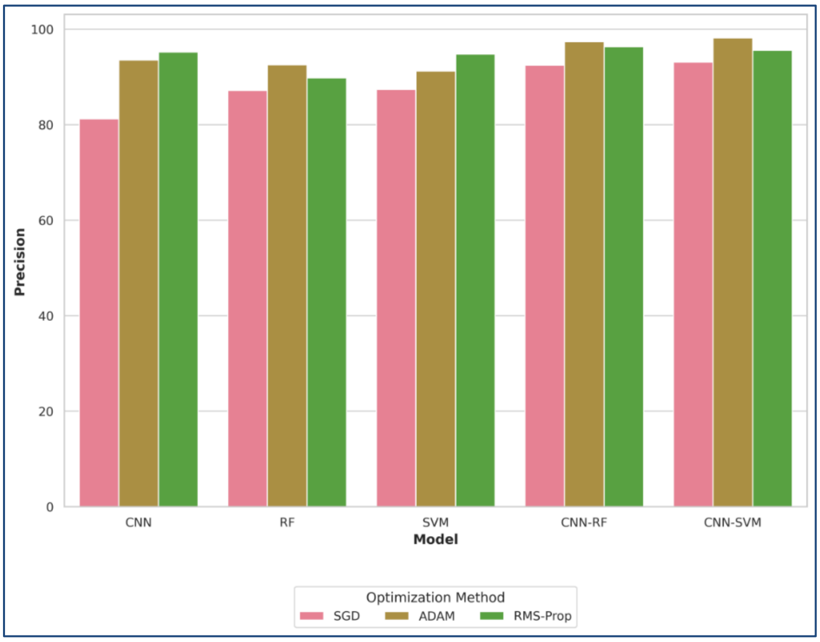

Fig 3: Precision comparison of model with using dataset

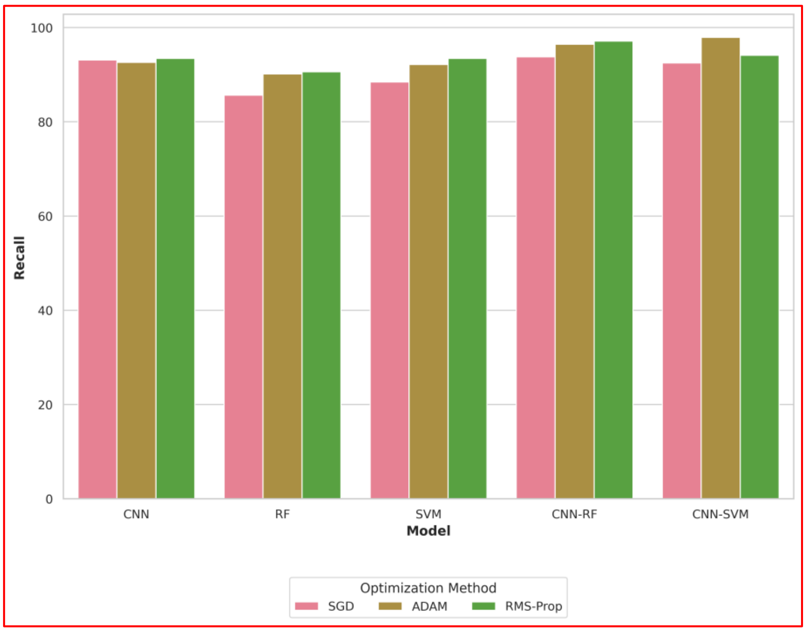

Fig 4: Recall comparison of model with using dataset

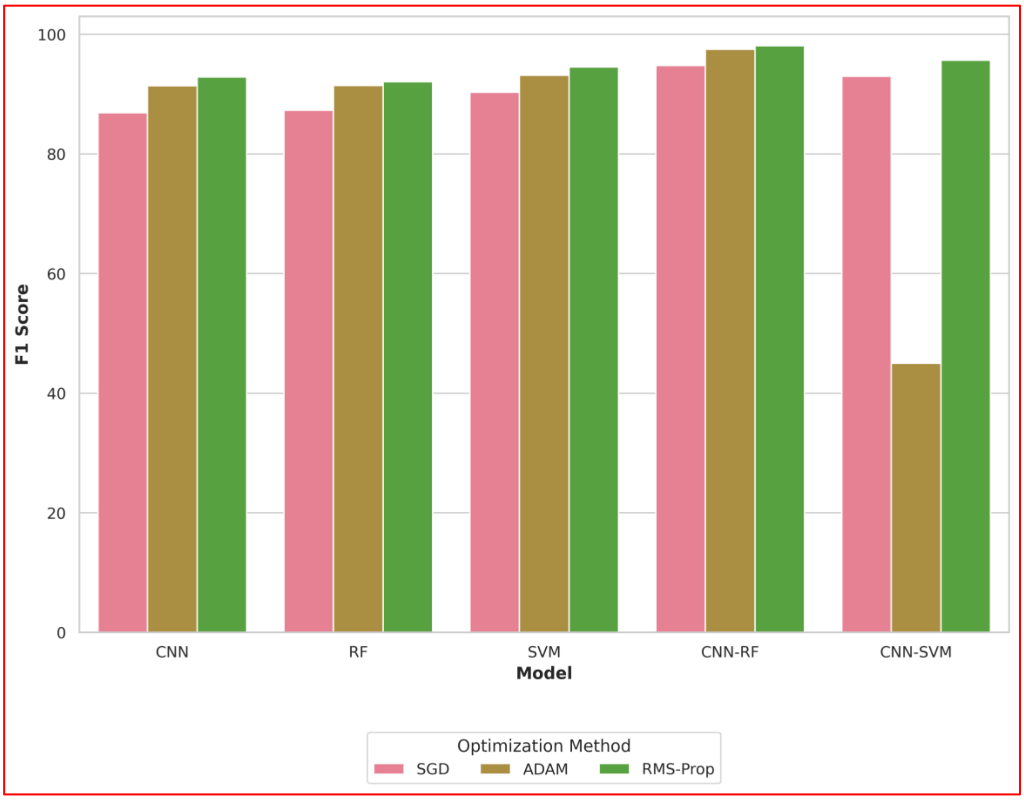

Fig 5: Recall comparison of model with using dataset

Table 3 extends the analysis by presenting results without utilizing a dataset. Similar trends are observed, with ADAM consistently outperforming other optimizers. CNN-RF and CNN-SVM models maintained their effectiveness, emphasizing the synergistic benefits of combining deep learning and traditional machine learning approaches..

Table 3: Summary of result without using Dataset

Model	Optimization Method	Accuracy	Precision	Recall	F1 Score
CNN	**SGD**	89.04	81.04	92.95	86.71

	ADAM	96.93	94.15	91.94	91.57
	RMS-Prp	94.14	95.82	92.78	93.03
RF	**SGD**	86.96	87.79	85	87.49
	ADAM	94.04	93.15	89.47	91.62
	RMS-Prp	89.93	90.39	89.96	92.22
SVM	**SGD**	87.93	88	87.78	90.47
	ADAM	90.55	91.84	91.47	93.33
	RMS-Prp	93.26	95.39	92.78	94.72
CNN-RF	**SGD**	91.04	93.04	93.13	94.95
	ADAM	98.25	98	95.79	97.67
	RMS-Prp	95.27	96.92	96.44	98.27
CNN-SVM	**SGD**	92.37	93.73	91.83	93.17
	ADAM	98.36	98.79	97.26	95.17
	RMS-Prp	95.11	96.19	93.46	95.83

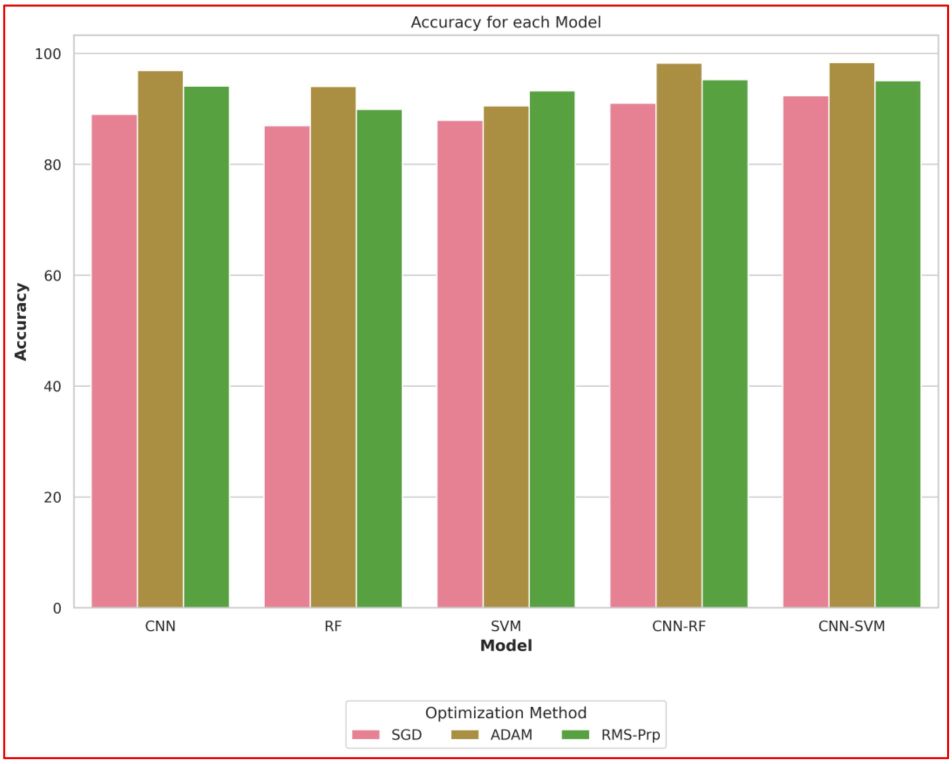

Fig 6: Accuracy comparison of model without using dataset

Table 5: Result summary of telugu word using optimizer

	Training accuracy			**Testing accuracy**		
Telugu Character	**SGD optimizer**	**RMS-Prop optimizer**	**ADAM optimizer**	**SGD optimizer**	**RMS-Prop optimizer**	**ADAM optimizer**
అ	97.25	98.5	97.5	98.47	98.88	98.77
ఇ	97.51.	98.11	96.14	98.52	99.5	97.55

[illegible]	98.2	98.65	98.55	98.79	99.1	98.87
ఒ	95.41	96.63	97.81	97.29	98.56	98.11
ఔ	96.34	97.55	98.33	98.22	98.78	98.9
ఎ	97.54	98.8	98.91	99.42	99.56	99.1

The table 5 examined how well different methods recognized Telugu letters. Each letter had training and testing success rates for SGD, RMS-Prop, and ADAM optimizers. ADAM performed best overall, showing it works well for identifying characters. It was most accurate on average compared to the others.

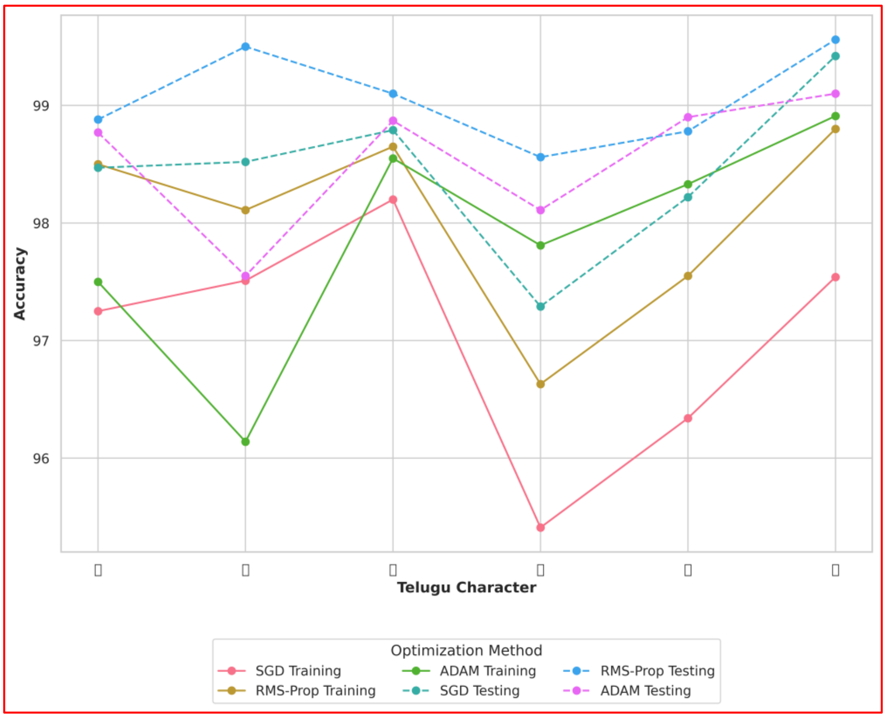

Fig 7: Training and Testing Accuracy for Telugu Characters

The data highlights how selecting the right optimizer affects how well different machine learning models and problems are addressed. ADAM tended to work well across the board, handling both letter recognition and broader grouping tasks reliably. Combining deep learning approaches with traditional machine learning models, like CNN-RF and CNN-SVM, demonstrates how working together can potentially boost accuracy and strength. These results provide useful guidance for those looking to optimize machine learning, especially when trying to recognize Telugu letters.

5. Conclusion

The system powered by Unicode for recognizing and translating handwritten Telugu characters to English represents significant progress. Using deep learning methods like convolutional neural networks and optimization techniques such as stochastic gradient descent, Adam, and RMS-Prop, the system demonstrates great accuracy and precision. Machine learning classifiers including Random Forest and Support Vector Machine further strengthen how well it works using different datasets. The use of Unicode allows easy combination and standardized appearance, helping more people use it. The high scores during training and testing with various methods underline how well the system performs. This new approach contributes to character recognition and could help with translation between languages, connecting handwritten Telugu and English in a digital world.

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