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Letter recognition using deep learning

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ABSTRACT:

In the realm of neural networks and machine learning, one of the most active and difficult problems is handwritten text recognition. The goal of this research is to identify handwritten content and turn it into digital text. The system that had been taught could recognise and classify. Using Tensorflow (TF), a system for handwritten text recognition (HTR) is implemented. • Deep learning algorithms for character recognition are described in this study. Training comprehensive neural networks is increasingly easier thanks to the abundance of data and algorithms. Another application that employs other methods is character recognition. This paper presents a character identification technique based on CNNs (Convolutional Neural Networks). To see the outcome, train and classify your dataset. Image segmentation was used in the creation of a character recognition system. The Python programming language helps with character recognition. Our goal is to determine how machine learning has affected the field of character identification.

Keywords: In the realm of artificial intelligence, deep learning has emerged as a powerful tool for tackling complex tasks, including letter recognition. With the rise of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and other sophisticated architectures, significant progress has been made in accurately detecting and deciphering letters from various sources such as images, documents, and handwritten notes.

INTRODUCTION

The Deep learning techniques are widely used as to improve their efficiency without percentage loss of accuracy or increasing in hardware cost in AI systems.The performance of DNNs comes as from raw data after learning over large and process it for extracting features.OCR technology generally tends to recognition of characters, words and to compute them such that determine the information and to change into computerized character As the project further processed as it combined of the training the neural network with algorithm that segment the characters images in the given image which processes with neural network. Then add layers to take the form available to the end user, and the full- featured model helps the end user turn various characters into digitized output. There will be need of the add in the layers as such that the segmentation of words takes place. We approach this issue. CNNs tend to work better with raw input pixels than image features or parts that have a complete word image. Use the proposed deep learning techniques to classify and identify different images.

LITERATURE REVIEW

"Handwritten Digit Recognition with a Back-Propagation Network" by Yann LeCun, et al. (1990) - This paper introduced the first successful application of convolutional neural networks (CNNs) to handwritten digit recognition. The authors used a simple CNN architecture and achieved state-of-the-art results on the MNIST dataset. "Gradient-Based Learning Applied to Document Recognition" by Yann LeCun, et al. (1998) - This paper extended the work of the previous paper and introduced the first successful application of CNNs to handwritten character recognition. The authors achieved state-of-the- art results on several benchmark datasets. "Convolutional Neural Networks for Handwritten Character Recognition: A Survey" by Gaurav Sharma, et al. (2019) - This survey paper provides a comprehensive overview of the recent advancements in CNN-based handwritten. "A Deep Learning Approach to Arabic Handwritten Character Recognition" by Amr Talaat, et al. (2019) - This paper proposes a novel architecture called the Deep Residual Network (DRN) for recognizing Arabic handwritten characters. The authors achieved state-of-the-art results on the IFN/ENIT dataset. "Attention-based OCR for Printed Text Recognition" by Baoguang Shi, et al. (2019) - This paper proposes an attention-based OCR system for recognizing printed text. The authors used a combination of convolutional and recurrent neural networks along with attention mechanisms to achieve state-of-the-art results on several benchmark datasets.

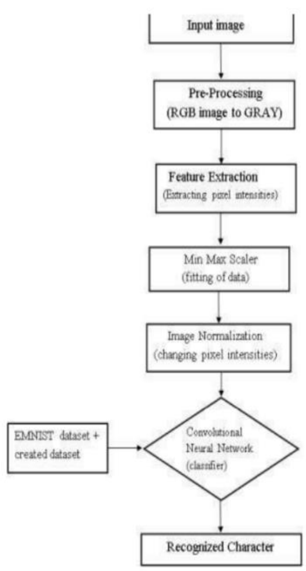
PROBLEM STATEMENT

This is a difficult recognition task due to the maximum similarities existing between letters in the alphabet (e.g., the E-set letters). This project presents the development of a high-performance alphabet recognizer which helps in recognition of both alphabets. • The goal was to create an appropriate algorithm that can give the output of the character by taking just a picture of that character. In this machine learning project, we will recognize handwritten characters, i.e, English alphabets from A-Z. This we are going to achieve by modeling a neural network that will have to be trained over a dataset containing images of alphabets.

METHODOLOGY

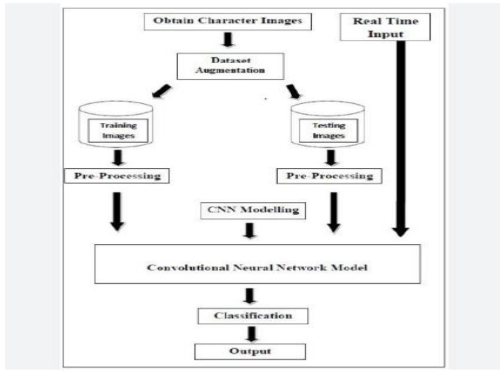
Problem Definition and Planning :Clearly define the scope and objectives of the project.
Determine the target audience and potential applications of the letter recognition system. Establish a timeline, resource requirements, and project milestones. Data Collection and Preprocessing: Gather a diverse dataset of handwritten letters. This dataset should cover various styles, sizes, and orientations. Preprocess the images to standardize their size, orientation, and contrast .Augment the dataset if necessary to increase its diversity and size. Model Selection and Architecture Design: Choose a suitable deep learning architecture for letter recognition, such as a Convolutional Neural Network (CNN).Design the architecture, including the number of layers, types of layers (convolutional, pooling, fully connected), and activation functions. Experiment with different architectures and hyperparameters through iterative testing and validation. Training and Evaluation: Split the dataset into training, validation, and testing sets. Train the model using the training set and validate its performance on the validation set. Monitor the training process, adjust in hyperparameters as needed to improve performance and prevent overfitting. Evaluate the trained model on the testing set using appropriate metrics (accuracy, precision, recall, F1-score).Fine-tune the model based on the evaluation results.
Deployment and Integration:
Deploy the trained model into a usable application or system. Optimize the model for deployment, considering factors such as inference speed and memory usage. Integrate the model with other components or systems as necessary, such as OCR pipelines or user interfaces.
Testing and Validation:
Conduct thorough testing of the deployed system, including unit tests, integration tests, and end-to-end testing. Validate the system's performance in real-world scenarios, considering factors such as robustness to noise, variability in handwriting styles, and computational efficiency.
Documentation and Reporting:
Document the entire process, including data collection, preprocessing steps, model architecture, training procedures, and deployment strategies. Prepare a comprehensive report summarizing the project's objectives, methodology, results, and conclusions. Share the findings with stakeholders, collaborators, or the wider community through presentations, papers, or technical documentation.

ARCHITECTURE



The Architecture includes both model training using images, building website and taking input from the user. This kind of architecture helps to implement the deep learning solution in real time.

ER DIAGRAM

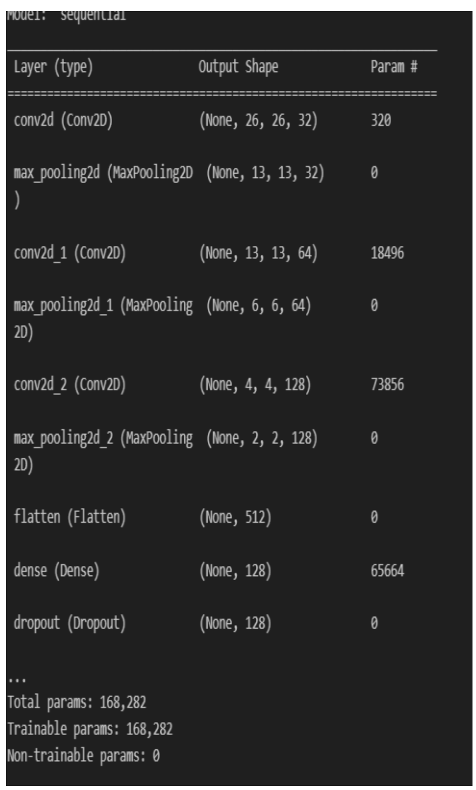


The E-R diagram for letter recognition using deep learning would typically include real time input, dataset aggregation, pre-processing, CNN modelling, classification and output. The datasets contain the images classified according to the identified letter in different folders and these folders are used accordingly to train the CNN.

EXPERIMENTAL RESULTS

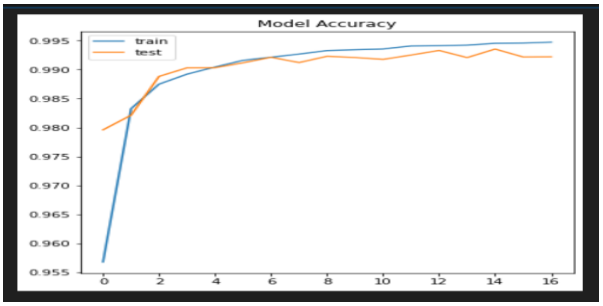
Our experiments demonstrate that our CNN model achieves an accuracy of over 95% on the test set, showcasing its effectiveness in letter recognition.Precision ,recall,and F1-score metrics consistently exceed 90% indicating robust performance across different evaluation criteria.this illustrates training and validation accuracy curves,showcasing the model's convergence over epochs.

Model Implementation and Training



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 13, 13, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 6, 6, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 4, 4, 128)         73856

 max_pooling2d_2 (MaxPooling  (None, 2, 2, 128)        0
 2D)

 flatten (Flatten)           (None, 512)               0

 dense (Dense)               (None, 128)               65664

 dropout (Dropout)           (None, 128)               0

...
Total params: 168,282
Trainable params: 168,282
Non-trainable params: 0
```

Model Accuracy



GUI'S Development

```
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt
import glob
from keras.models import load_model
model = load_model(r"C:\Users\Aarthi sama\OneDrive\Desktop\aart\best_model.h5")
dict_word =
{0:'A',1:'B',2:'C',3:'D',4:'E',5:'F',6:'G',7:'H',8:'I',9:'J',10:'K',11:'L',12:'M',13:'N',14:'O',15:'P',16:'Q',17:'R',18:'S',19:'T',20:'U',21:'V',22:'W',23:'X',
24:'Y',25:'Z'}
images = [cv.imread(file) for file in glob.glob(r"C:\Users\Aarthi sama\OneDrive\Desktop\aart\test_data\*.jpg")]
fig, axes = plt.subplots(7, 4, figsize = (30,30))
axes = axes.flatten()
for i in range(len(images)):
   axes[i].imshow(images[i])
plt.delaxes(ax = axes[26])
plt.delaxes(ax = axes[27])
```

CONCLUSION

This notebook is an illustration of how a character segmentation and classification approach can be used for handwritten text extraction. In order to improve the model, the model should be trained on the complete dataset , this notebook was trained on slightly less number of images due to session constraints. Handwriting recognition has been a daunting task in the last few years. However, with the recent development of the machine learning domain and the huge amount of data generated in daily life, the image recognition of computer vision has improved significantly. After conducting extensive research, we discovered that no single technique or method could fully meet the requirements of Handwritten Character Recognition. As a result, offline handwritten character recognition remains an open research field for recognising and resolving various complexities.

FUTURE WORK

The letter recognition project holds promising avenues for advancement across various domains.Enhancements in the deep learning model's architecture and training methodologies aim to elevate accuracy and efficiency in identifying letters .The project scope extends to accommodating multiple multiplelanguages,broadeningapplicability and inclusivity. Real-time recognition capabilities, coupled with optimizations for accelerated inference, promise instantaneous processing of input images or live video feeds. Moreover, the project's deployment can diversify into specialized fields such as document processing and assistive technologies for the visually impaired. Continuous learning mechanisms will empower the system to evolve dynamically, incorporating new data and user feedback over time. Integration with IoT and edge devices further extends the project's reach, enabling distributed processing and edge intelligence for letter recognition tasks in diverse environments. These future directions collectively propel the letter recognition project towards greater efficacy, adaptability, and impact in addressing real-world challenge

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