PROJECT REPORT

ARTIFICIAL INTELLIGENCE

A NOVEL METHOD FOR HANDWRITTENDIGIT RECOGNITION SYSTEM

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INTRODUCTION

1.1 PROJECT OVERVIEW

Machine learning and deep learning play an important role in computer technology and artificial intelligence. With the use of deep learning and machine learning, human effort can be reduced in recognizing, learning, predictions and in many more areas.

Handwritten Digit Recognition is the ability of computer systems to recognise handwritten digits from various sources, such as images, documents, and so on. This project aims to let users take advantage of machine learning to reduce manual tasks in recognizing digits.

1.2 PURPOSE

Digit recognition systems are capable of recognizing the digits from different sources like emails, bank cheque, papers, images, etc. and in different real-world scenarios for online handwriting recognition on computer tablets or system, recognize number plates of vehicles, processing bank cheque amounts, numeric entries in forms filled up by hand (tax forms) and so on.

Handwritten digit recognition is the process to provide the ability to machines to recognize human handwritten digits. It is not an easy task for the machine because handwritten digits are not perfect, vary from person-to-person, and can be made with many different flavors.

LITERATURE SURVEY

2.1 EXISTING PROBLEM

The fundamental problem with handwritten digit recognition is that handwritten digits do not always have the same size, width, orientation, and margins since they vary from person to person. Additionally, there would be issues with identifying the numbers because of similarities between numerals like 1 and 7, 5 and 6, 3 and 8, 2 and 5, 2 and 7, etc. Finally, the individuality and variation of each individual's handwriting influence the structure and appearance of the digits.

2.2 REFERENCES

Improved Handwritten Digit Recognition Using Convolutional Neural Networks (CNN) (2020):

This paper's primary goal was to enhance handwritten digit recognition ability. To avoid difficult pre-processing, expensive feature extraction, and a complex ensemble (classifier combination) method of a standard recognition system, they examined different convolutional neural network variations. Their current work makes suggestions on the function of several hyper- parameters through thorough evaluation utilizing an MNIST dataset. They also confirmed that optimizing hyper-parameters is crucial for enhancing CNN architecture performance. With the Adam optimizer for the MNIST database, they were able to surpass many previously published results with a recognition rate of 99.89%. Through the trials, it is made abundantly evident how the performance of handwritten digit recognition is affected by the number of convolutional layers in CNN architecture. According to the paper, evolutionary algorithms can be explored for optimizing convolutional filter kernel sizes, CNN learning parameters, and the quantity of layers and learning rates.

An Efficient and Improved Scheme for Handwritten Digit Recognition Based on Convolutional Neural Network (2019):

This study uses rectified linear units (RELU) activation and a convolutional neural network (CNN) that incorporates the Deeplearning4j (DL4J) architecture to recognize handwritten digits. The proposed CNN framework has all the necessary parameters for a high level of MNIST digit classification accuracy. The system's training takes into account the time factor as well. The system is also tested by altering the number of CNN layers for additional accuracy verification. It is important to note that the CNN architecture consists of two convolutional layers, the first with 32 filters and a 5x5 window size and the second with 64 filters and a 7x7 window size. In comparison to earlier proposed systems, the experimental findings show that the proposed CNN architecture for the MNIST dataset demonstrates great performance in terms of time and accuracy. As a result, handwritten numbers are detected with a recognition rate of 99.89% and high precision (99.21%) in a short amount of time.

Improved Handwritten Digit Recognition Using Quantum K-Nearest Neighbour Algorithm (2019):

The KNN classical machine learning technique is used in this research to enable quantum parallel computing and superposition. They used the KNN algorithm with quantum acceleration to enhance handwritten digit recognition. When dealing with more complicated and sizable handwritten digital data sets, their suggested method considerably lowered the computational time complexity of the traditional KNN algorithm. The paper offered a theoretical investigation of how quantum concepts can be applied to machine learning.

Handwritten Digit Recognition Using Machine and Deep Learning Algorithms (2021):

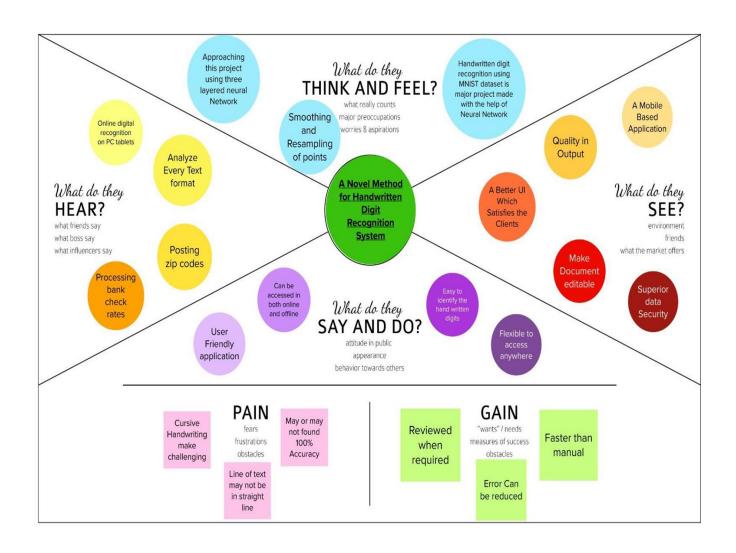
In this study, they developed three deep and machine learning-based models for handwritten digit recognition using MNIST datasets. To determine which model was the most accurate, they are compared them based on their individual properties. Support vector machines are among the simplest classifiers, making them faster than other algorithms and providing the highest training accuracy rate in this situation. However, due to their simplicity, SVMs cannot categorize complicated and ambiguous images as accurately as MLP and CNN algorithms can. In their research, they discovered that CNN produced the most precise outcomes for handwritten digit recognition. This led them to the conclusion that CNN is the most effective solution for all types of prediction issues, including those using picture data. Next, by comparing the execution times of the algorithms, they determined that increasing the number of epochs without changing the configuration of the algorithm is pointless due to the limitation of a certain model, and they discovered that beyond a certain number of epochs, the model begins over- fitting the dataset and provides biased predictions.

2.3 PROBLEM STATEMENT DEFINITION

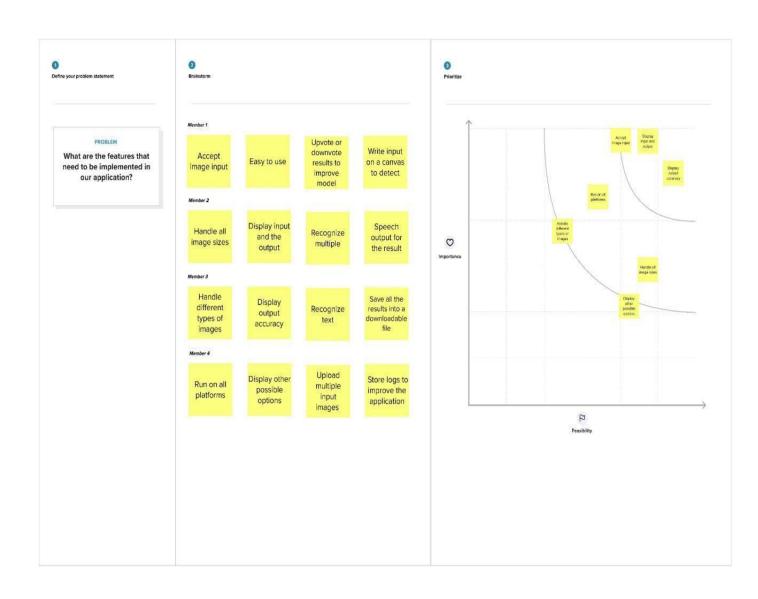
For years, the traffic department has been combating traffic law violators. These offenders endanger not only their own lives, but also the lives of other individuals. Punishing these offenders is critical to ensuring that others do not become like them. Identification of these offenders is next to impossible because it is impossible for the average individual to write down the license plate of a reckless driver. Therefore, the goal of this project is to help the traffic department identify these offenders and reduce traffic violations as a result.

IDEATION AND PROPOSED SOLUTION

3.1. EMPATHY MAP CANVAS



3.2 IDEATION & BRAINSTORMING

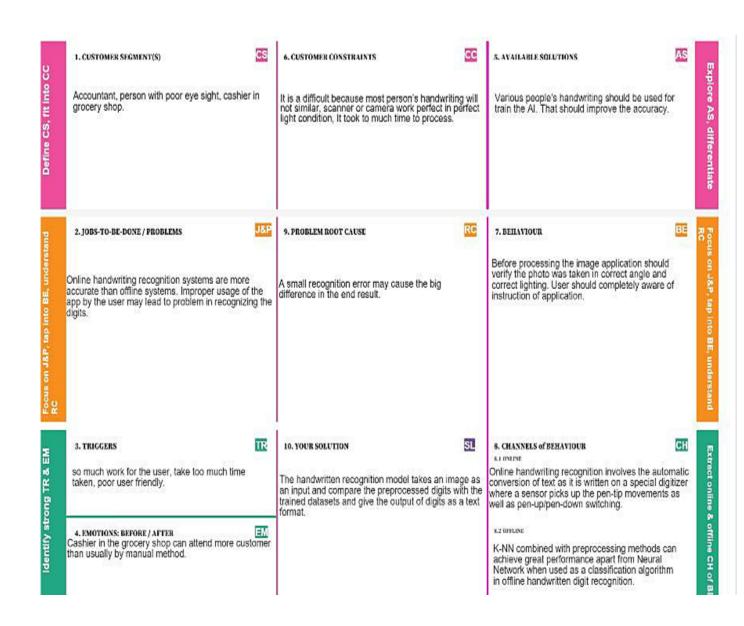


3.3 PROPOSED SOLUTION

S.NO	PARAMETER	DESCRIPTION
1	Problem Statement	An optimized way to recognize and predict the handwritten digit with increased accuracy (expecting to achieve results more than 97% accuracy), low run time and low memory requirements.
2	Idea / Solution description	The idea is to calculate features that make it possible to distinguish between different numbers. Some example features for this dataset might include the number of colour pixels, or maybe the width and the height of the digits and use the SVMS algorithm to optimize the prediction.

3	Novelty / Uniqueness	Precisely recognise and predict the uploaded document and canvas drawn digits using the SVMS algorithm and the feature extraction aspect
4	Social Impact / Customer Satisfaction	It helps the postal department, banking sector and traffic department.It also helps the old age humans with less eye sight
5	Business Model	We can generate revenue by advertisement part of our website and application play store revenue. We are aiming to collaborate with banking sectors, postal sectors and traffic control department to use our project in recognising cheque digits, zip code and number plate digit.
6	Scalability of the Solution	The scalability of our solution is to get accuracy of around 97% or more and also to grow exponentially in revenue.

3.4 PROBLEM SOLUTION FIT



REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENTS

FR-1	Image Data: Handwritten digit recognition refers to a computer's capacity to identify human handwritten digits from a variety of sources, such as photographs, documents, touch screens, etc., and categorize them into ten established classifications (0-9). In the realm of deep learning, this has been the subject of countless studies.
FR-2	Website: Web hosting makes the code, graphics, and other items that make up a website accessible online. A server hosts every website you've ever visited. The type of hosting determines how much space is allotted to a website on a server. Shared, dedicated, VPS, and reseller hosting are the four basic varieties.

FR-3	Cloud: The cloud offers a range of IT services, including virtual storage, networking, servers, databases, and applications. In plain English, cloud computing is described as a virtual platform that enables unlimited storage and access to your data over the internet.
FR-4	Modified National Institute of Standards and Technology dataset: The abbreviation MNIST stands for the MNIST dataset. It is a collection of 60,000 tiny square grayscale photographs, each measuring 28 by 28, comprising handwritten single digits between 0 and 9.

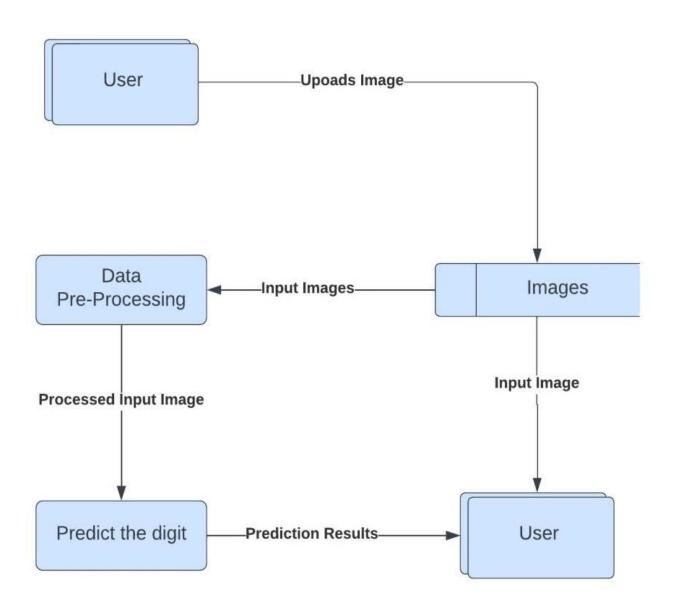
4.2 NON-FUNCTIONAL REQUIREMENTS

NFR	NON-FUNCTIONAL REQUIREMENTS	DESCRIPTION
NFR-1	Usability	One of the very significant problems in pattern recognition applications is the recognition of handwritten characters. Applications for digit recognition include filling out forms, processing bank checks, and sorting mail.
NFR-2	Security	The system generates a thorough description of the instantiation parameters, which might reveal information like the writing style, in addition to a categorization of the digit.

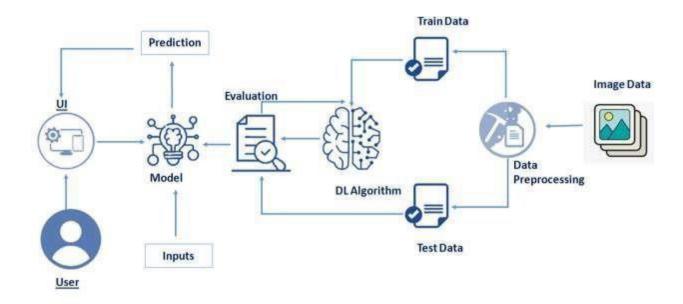
		The generative models are capable of segmentation driven by recognition. The procedure uses a relatively.
NFR-3	Reliability	The samples are used by the neural network to automatically deduce rules for reading handwritten digits. Furthermore, the network may learn more about handwriting and hence enhance its accuracy by increasing the quantity of training instances. Numerous techniques and algorithms, such as Deep Learning/CNN, SVM, Gaussian Naive Bayes, KNN, Decision Trees, Random Forests, etc., can be used to recognize handwritten numbers.
NFR-4	Accuracy	With typed text in high-quality photos, optical character recognition (OCR) technology offers accuracy rates of greater than 99%. However, variances in spacing, abnormalities in handwriting, and the variety of human writing styles result in less precise character identification.
NFR-5	Scalability	The task of handwritten digit recognition, using a classifier, has great importance. The application must scale along with the user base.

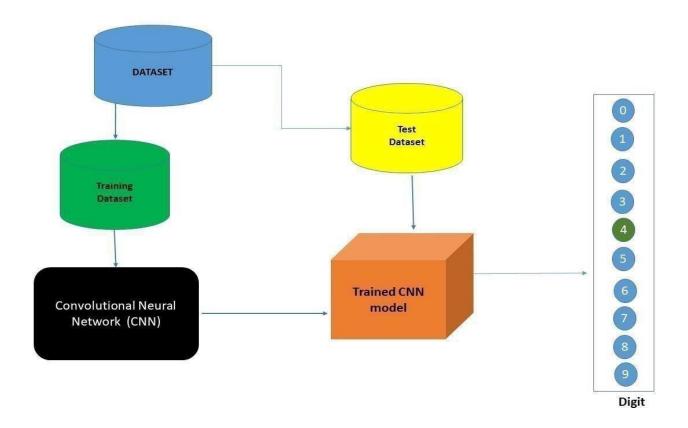
PROJECT DESIGN

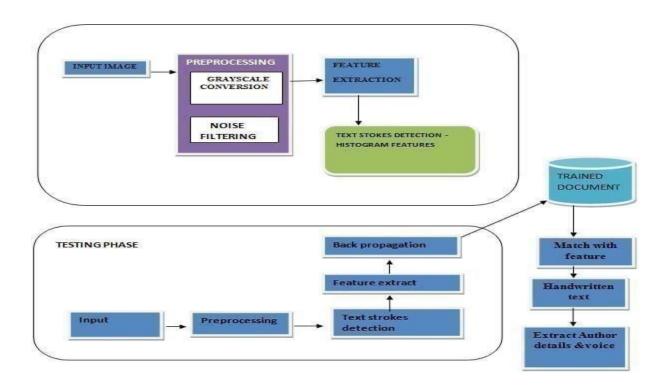
5.1 DATA FLOW DIAGRAM



5.2 SOLUTION & TECHNICAL ARCHITECTURE







USER STORIES:

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer Care Executive		USN-8	As a user I will train and test the input to get the ccuracy of output	I can able to train and test the application until it gets maximum accuracy of the result.	High	SPRINT-4
Administrator	Launch	USN-9	As a user, I can upload my handwritten digit images to be	I can choose and upload the image from the system storage and also in any virtual storage.	Medium	SPRINT-3

		recognised from the computer			
	USN-10	I can scan one page at once	I can get the recognised digits from the input given.	High	SPRINT-4
Recognize	USN-11	As a user I can turn on the camera using the input button.	I can get the input to be digitized.	High	SPRINT-3
	USN-12	As a user, I can use the web application virtually anywhere.	I can use the application portably anywhere.	High	SPRINT-2
	USN-13	As it is open source,i can use it cost freely.	I can use it without any payment to be paid for it to access	Medium	SPRINT-2

PROJECT PLANNING AND SCHEDULING

6.1 SPRINT PLANNING AND ESTIMATION

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	USER STORY	Priority	Team Members
Sprint-1	Dashboard	USN-1	A user, they can see the information regarding theprediction of handwritten digit recognition.	2	High	Akshaya R Saranya P Nagalakshmi K Janani M
Sprint-1	Launch	USN-2	On clicking the launch button, it will redirect the user to a page where the images to be predicted can be uploaded.	2	High	Akshaya R Saranya P Nagalakshmi K
Sprint-2	Upload	USN-3	Users can select the image from the localstorage.	2	High	Akshaya R Saranya P Janani M
Sprint-3	Predict	USN-4	Once the image is uploaded, it will predictthe respective image.	2	High	Akshaya R Saranya P
Sprint-4	Display	USN-5	The predicted image will be displayed with theaccuracy chart.	2	High	Akshaya R Saranya P Janani M

6.2 SPRINT DELIVERY SCHEDULE

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)		Sprint Release Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-3	20	6 Days	07 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	20	19 Nov 2022

CODING & SOLUTIONING

```
# Import necessary packages
import os
import random
import string
from pathlib import Path
import numpy as np
from tensorflow.keras.models import load_model
from PIL import Image, ImageOps
```

```
def random_name_generator(n: int) -> str:
    """
    Generates a random file name.

Args:
    n (int): Length the of the file name.

Returns:
    str: The file name.

"""

return ''.join(random.choices(string.ascii_uppercase + string.digits, k=n))
```

CHAPTER 8 TESTING

8.1 TEST CASES

Test case ID	Feature Type	Component	Test Scenario Expected Result		Actual Result	Status
HP_TC_00	UI	Home Page	Verify UI elements in the Home Page	The Home page must be displayed properly	Working as expected	PASS
HP_TC_002	UI	Home Page	Check if the UI elements are displayed properly in different screen sizes	The Home page must be displayed properly in all sizes	The UI is not displayed properly in screen size 2560 x 1801 and 768 x 630	FAIL
HP_TC_003	Functional	Home Page	Check if user can upload their file	The input imageshould be uploaded to the application successfully	Working as expected	PASS
HP_TC_004	Functional	Home Page	Check if user cannot upload unsupported files	The application should not allow user to select a non- image file	User is able to upload anyfile	FAIL
HP_TC_005	Functional	Home Page	Check if the page redirectsto the result page once theinput is given	The page shouldredirect to the results page	Working as expected	

BE_TC_00 1	Functional	Backend	Check if alltheroutes are workingproperly	All the routes should properlywork	Working as expected	PASS
M_TC_001	Functional	Model	Check if the modelcan handle various imagesizes	The model shouldrescale the image and predict the results	Working as expected	PASS
M_TC_002	Functional	Model	Check if the modelpredicts the digit	The model should predict the number	Working as expected	PASS
M_TC_003	Functional	Model	Check if themodel can handle complexinput image	The model shouldpredict the number in the compleximage	The model failsto identify the digit since the model is not builtto handle such data	FAIL
RP_TC_001	UI	Result Page	Verify UI elements inthe Result Page	The Result page must be displayed properly	Working as expected	PASS
RP_TC_00 2	UI	Result Page	Check if the input imageisdisplayed properly	The input image should be displayed properly	The size of the input image exceeds the display container	FAIL
RP_TC_00 3	UI	Result Page	Check if theresult is displayedproperly	The result should bedisplayed properly	Working as expected	PASS

8.2 USER ACCEPTANCE TESTING

8.2.1 DEFECT ANALYSIS

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Total
By Design	1	0	1	0	2
Duplicate	0	0	0	0	0
External	0	0	2	0	2
Fixed	4	1	0	1	6
Not Reproduced	0	0	0	1	1
Skipped	0	0	0	1	1
Won't Fix	1	0	1	0	2
Total	6	1	4	3	14

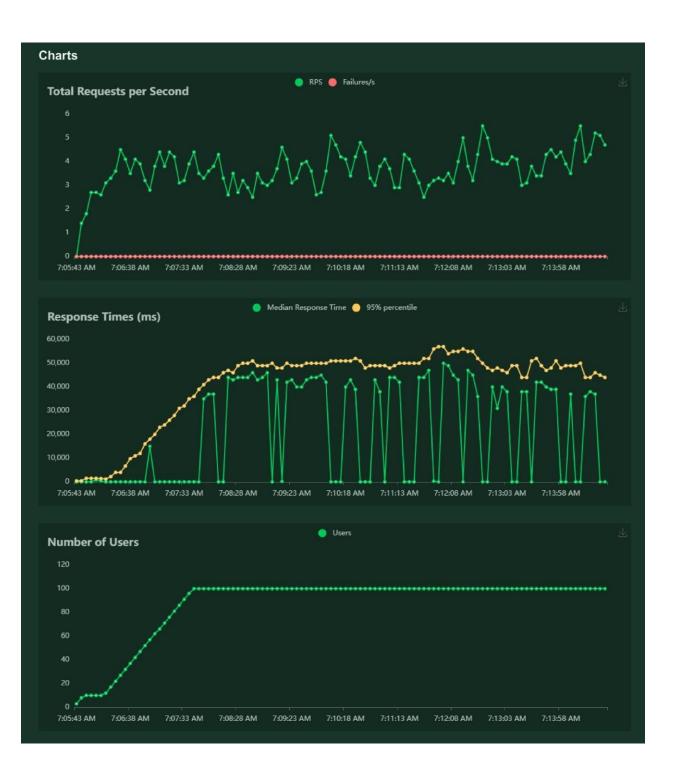
8.2.2 TEST CASE ANALYSIS

Section	Tota l Cases	Not Tested	Fail	Pass
Client Application	10	0	3	7
Security	2	0	1	1
Performance	3	0	1	2
Exception Reporting	2	0	0	2

RESULTS

9.1 PERFORMANCE METRICS

Locust Test Report During: 11/12/2022, 7:05:40 AM - 11/12/2022, 7:14:47 AM Target Host: http://127.0.0.1:5000/ Script: locust.py **Request Statistics** Method Name # Requests # Fails Average (ms) Min (ms) Max (ms) Average size (bytes) **RPS** Failures/s GET 1043 1079 GET //predict 1005 39648 385 59814 2670 1.8 0.0 2048 0 19462 4 59814 1859 3.7 0.0 Aggregated **Response Time Statistics** Method Name 50%ile (ms) 60%ile (ms) 70%ile (ms) 80%ile (ms) 90%ile (ms) 95%ile (ms) 99%ile (ms) 100%ile (ms) GET 19 22 62 290 55000 GET //predict 44000 46000 47000 48000 50000 52000 60000 36000 43000 45000 48000 50000 54000 60000 Aggregated 36



ADVANTAGES & DISADVANTAGES

ADVANTAGES:

- Reduces manual work
- More accurate than average human
- Capable of handling a lot of data
- Can be used anywhere from any device

DISADVANTAGES:

- Cannot handle complex data
- All the data must be in digital format
- Requires a high-performance server for faster predictions
- Prone to occasional errors

CONCLUSION

This project demonstrated a web application that uses machine learning to recognise handwritten numbers. Flask, HTML, CSS, JavaScript, and a few other technologies were used to create this project. The model predicts the handwritten digit using a CNN network. During testing, the model achieved a 99.61% recognition rate. The proposed project is scalable and can easily handle a huge number of users.

Since it is a web application, it is compatible with any device that can run a browser. This project is extremely useful in real-world scenarios such as recognizing number plates of vehicles, processing bank cheque amounts, numeric entries in forms filled up by hand (tax forms) and so on. There is so much room for improvement, which can be implemented in subsequent versions.

FUTURE SCOPE

This project is far from complete and there is a lot of room for improvement. Some of the improvements that can be made to this project are as follows:

- Add support to detect from digits multiple images and save the results
- Add support to detect multiple digits
- Improve model to detect digits from complex images
- Add support to different languages to help users from all over the world

This project has endless potential and can always be enhanced to become better. Implementing this concept in the real world will benefit several industries and reduce the workload on many workers, enhancing overall work efficiency.

Future development of the applications based on algorithms of deep and machine learning is practically boundless. In the future, we can work on a denser or hybrid algorithm than the current set of algorithms with more manifold data to achieve the solutions to many problems.

APPENDIX

SOURCE CODE MODEL CREATION:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.utils import np_utils
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Dense, Flatten
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import load_model
from PIL import Image, ImageOps
(X_train, y_train), (X_test, y_test) = mnist.load_data()
X_train = X_train.reshape(60000, 28, 28, 1).astype('float32')
X_test = X_test.reshape(10000, 28, 28, 1).astype('float32')
number_of_classes = 10
Y_train = np_utils.to_categorical(y_train, number_of_classes)
Y_test = np_utils.to_categorical(y_test, number_of_classes)
```

```
# Create the model
model = Sequential()
model.add(conv2D(64, (3, 3), input_shape=(28, 28, 1), activation="relu"))
model.add(Conv2D(32, (3, 3), activation="relu"))
model.add(FLatten())
model.add(Dense(number_of_classes, activation="softmax"))

model.compile(Loss='categorical_crossentropy', optimizer="Adam", metrics=["accuracy"])

# Train the model
model.fit(X_train, Y_train, batch_size=32, epochs=5, validation_data=(X_test,Y_test))

# Evaluate the model
metrics = model.evaluate(X_test, Y_test, verbose=0)
print("Metrics (Test Loss & Test Accuracy): ")
print(metrics)

# Save the model
model.save("model.h5")
```

```
# Test the saved model
model=load_model("model.h5")

img = Image.open("sample.png").convert("L")
img = img.resize((28, 28))
img2arr = np.array(img)
img2arr = img2arr.reshape(1, 28, 28, 1)
results = model.predict(img2arr)
results = np.argmax(results,axis = 1)
results = pd.Series(results,name="Label")
print(results)
```

FLASK APP:

```
from flask import Flask,render_template,request
from recognizer import recognize

app=Flask(__name__)

@app.route('/')
def main():
    return render_template("home.html")

@app.route('/predict',methods=['POST'])
def predict():
    if request.method=='POST':
        image = request.files.get('photo', '')
        best, others, img_name = recognize(image)
        return render_template("predict.html", best=best, others=others, img_name=img_name)

if __name__=="__main__":
    app.run()
```

RECOGNIZER:

```
# Import necessary packages
import os
import random
import string
from pathlib import Path
import numpy as np
from tensorflow.keras.models import load_model
from PIL import Image, ImageOps
```

```
def random_name_generator(n: int) -> str:
    """
    Generates a random file name.

Args:
    n (int): Length the of the file name.

Returns:
    str: The file name.

"""
    return ''.join(random.choices(string.ascii_uppercase + string.digits, k=n))
```

```
def recognize(image: bytes) -> tuple:
   model=load_model(Path("./model/model.h5"))
    img = Image.open(image).convert("L")
    img_name = random_name_generator(10) + '.jpg'
    img.save(Path(f"./static/data/{img_name}"))
    img = ImageOps.grayscale(img)
    img = ImageOps.invert(img)
    img = img.resize((28, 28))
    img2arr = np.array(img)
    img2arr = img2arr / 255.0
    img2arr = img2arr.reshape(1, 28, 28, 1)
    results = model.predict(img2arr)
    best = np.argmax(results,axis = 1)[0]
    pred = list(map(lambda x: round(x*100, 2), results[0]))
    others = list(zip(values, pred))
    best = others.pop(best)
   return best, others, img_name
```

HOME PAGE (HTML):

```
<meta name="viewport" content="width=device-width, initial-scale=1.0" />
<title>Handwritten Digit Recognition</title>
<link rel="icon" type="image/svg" sizes="32x32" href="{{url_for('static',filename='images/icon.svg')}}"</pre>
<link rel="stylesheet" href="{{url_for('static',filename='css/main.css')}}" />
<script src="https://unpkg.com/feather-icons"></script>
<script defer src="{{url_for('static',filename='js/script.js')}}"></script>
<div class="container">
    <div class="heading">
        <h1 class="heading_main">Handwritten Digit Recognizer</h1>
        <h2 class="heading_sub">Easily analyze and detect handwritten digits</h2>
    <div class="upload-container">
        <div class="form-wrapper">
            <form class="upload" action="/predict" method="post" enctype="multipart/form-data">
                <label id="label" for="upload-image"><i data-feather="file-plus"></i>Select File</label>
                <input type="file" name="photo" id="upload-image" hidden />
                <button type="submit" id="up_btn"></button>
            <img id="loading" src="{{url_for('static',filename='images/loading.gif')}}">
```

HOME PAGE (CSS):

```
@import url("https://fonts.googleapis.com/css2?family=Overpass:wght@200;300;400;500;600;700;900&display=swap");

* {
    padding: 0;
    margin: 0;
}

body {
    color: black;
    font-family: "Overpass", sans-serif;
}
```

HOME PAGE(JS):

```
feather.replace(); // Load feather icons

form = document.querySelector('.upLoad')
loading = document.querySelector("#Loading")
select = document.querySelector("#upLoad-image");

select.addEventListener("change", (e) => {
    e.preventDefault();
    form.submit()
    form.style.visibility = "hidden";
    loading.style.display = 'flex';
});
```

PREDICT PAGE (HTML):

```
<title>Prediction | Handwritten Digit Recognition</title>
<link rel="stylesheet" href="{{url_for('static',filename='css/predict.css')}}" />
k rel="icon" type="image/svg" sizes="32x32" href="{{url_for('static',filename='images/icon.svg')}}"
<meta name="viewport" content="width=device-width, initial-scale=1.0" />
<div class="container">
    <h1>Prediction</h1>
    <div class="result-wrapper">
        <div class="input-image-container">
            <img src="{{url_for('static',filename='data/')}}{{img_name}}" />
        <div class="result-container">
            <div class="value">{{best.0}}</div>
            <div class="accuracy">{{best.1}}%</div>
    <h1>Other Predictions</h1>
    <div class="other_predictions">
        {% for x in others %}
        <div class="value">
            <h2>{{x.0}}</h2>
            <div class="accuracy">{{x.1}}%</div>
        {% endfor %}
```

```
.result-wrapper .input-image-container img {
.result-wrapper .result-container .value {
margin-top: -1rem;
}
.result-wrapper .result-container .accuracy {
.other_predictions {
   flex-wrap: wrap;
   column-gap: 1rem;
.other_predictions .value {
   width: 5rem;
    height: 5rem;
.other_predictions .value div {
   margin-top: -1.2rem;
@media screen and (max-width: 700px) {
       font-size: 2.3rem;
    .result-wrapper .input-image-container,
        height: 7rem;
      font-size: 4rem;
```

```
@import url("https://fonts.googleapis.com/css2?family=Overpass:wght@200;300;400;500;600;700;900&display=swap");
   font-family: "Overpass", sans-serif;
   padding-top: 2rem;
   justify-content: center;
   align-items: center;
.result-wrapper {
   width: -moz-fit-content;
   width: fit-content;
   height: -webkit-fit-content;
   height: -moz-fit-content;
   box-shadow: 0 0 10px rgb(126, 125, 125);
   padding: 1.5rem;
   justify-content: center;
   align-items: center;
   -moz-column-gap: 1rem;
   column-gap: 1rem;
.result-wrapper .input-image-container,
.result-wrapper .result-container {
   width: 15rem;
   height: 15rem;
   border: 1px dashed black;
   align-items: center;
   flex-direction: column;
   background-color: rgb(209, 206, 206);
```



https://github.com/IBM-EPBL/IBM-Project-45066-1660728115

PROJECT DEMO

https://www.youtube.com/embed/RJ5TfR8lQ-c