

HANDWRITTEN DIGIT RECOGNITION
TABLE OF CONTENTS

S.NO	TITLE	PAGE
1	Introduction	3
1.1	Project Overview	3
1.2	Purpose	3
2	Literature Survey	4
2.1	Existing problem	4
2.2	References	4
2.3	Problem Statement	5
3	Ideation & Proposed Solution	6
3.1	Empathy Map canvas	6
3.2	Ideation & Brainstorming	6
3.3	Proposed Solution	7
3.4	Problem Solution Fit	8
4	Requirement Analysis	8
4.1	Functional Requirement	8
4.2	Non-functional Requirement	9
5	Project Design	9
5.1	Data Flow Diagrams	9
5.2	Solution & Technical Architecture	10
5.3	User Stories	13
6	Project Planning & Scheduling	14

6.1	Sprint Planning & Estimation	14
6.2	Sprint Delivery Schedule	15
6.3	Reports from JIRA	15
7	Coding & Solutioning	16
7.1	Feature-1	16
7.2	Feature-2	16
8	Testing	16
8.1	Test Cases	16
8.2	User Acceptance Testing	17
9	Results	18
9.1	Performance Metrics	18
10	Advantages & Disadvantages	18
11	Conclusion	19
12	Future Scope	19
13	Appendix	20
	Source Code	20
	GitHub & Project Demo Link	28

1. INTRODUCTION

1.1. PROJECT OVERVIEW

Traditional methods of recognizing handwriting rely heavily on a lot of prior knowledge like Optical Character Recognition (OCR). Since the style of handwriting changes with every individual, it is a challenging task in identifying the characters correctly. The thickness of stroke, style carries uniqueness with different person depending on them. The rapid growth in the need for digitizing handwritten data and the availability of massive processing power demands improvement in recognition accuracy. Hence a highly proficient algorithm is required when dealing with handwriting recognition. Handwritten digit recognition can be done using deep learning methods effectively. The Convolutional Neural Networks (CNN) is a deep learning algorithm that is highly suitable for image recognition and those tasks involving processing of pixel data. MNIST data set is widely used for this recognition process and it has 70000 handwritten digits. Those images are split as train set and test set images. Artificial neural networks is used to train these images and build a deep learning model. Web application is created where the user can upload an image of a handwritten digit. this image is analysed by the deep learning model and the detected result as UI.

1.2. PURPOSE

Each individual has a unique handwriting style which makes it a bit complex to identify the digits. If the handwritten digit recognition becomes an efficient practice, this will help digitize number processing. Huge amounts of data can be processed by machine which will save loads of time. In today's world, technology plays a major role in handling data, therefore it is important to bring this system in managing data. Workers at the postal office sorting throughs mails using the postal code can be helped using this. This also comes handy while arranging records and huge amounts of information. Manual labour is eased and it saves up a lot of time. It can be used in programming checks and in case of tax documentation. The labour cost will also be reduced with the help of machines. There are also the activities of processing bank checks and tax documentations. Large piles of records and archives can be arranged and sorted well easing the stress and work load from manual labourers.

2. LITERATURE SURVEY

2.1. EXISTING PROBLEM

Because of the progress in science and technology everything is being digitalised to reduce human effort. It takes a lot of time and effort on the side of manual workers when sorting through mails by postal codes. It is not an easy task to handle data by human worker. There is also the possibility of human error while processing huge amount of data. Therefore, digitizing these will help reduce time and labour. The labour cost will also be reduced with the help of machines. There are also the activities of processing bank checks and tax documentations. Large piles of records and archives can be arranged and sorted well easing the stress and work load from manual labourers. The problem with handwriting is that every individual has different style of writing. There is a differing thickness of stroke, style and general uniqueness that just brings a level of hardness in identifying the handwriting. The machine must be capable of picking up the digits correctly with a good accuracy rate. Hence a highly proficient algorithm is required when dealing with handwriting recognition. Handwritten digit recognition can be done using deep learning methods effectively.

2.2. REFERENCES

- [1] Handwritten Digit Recognition using Machine and Deep Learning Algorithms by Ritik Dixit of Computer Science and Engineering, Rishika Kushwah of Computer Science and Engineering, Samay Pashine of Computer Science and Engineering, Acropolis Institute of Technology & Research, Indore, India, 23 June 2021
- [2] Recognition of Handwritten Digit using Convolutional Neural Network (CNN), By Md. Anwar Hossain & Md. Mohon Ali, Pabna University of Science & Technology, 2019
- [3] On the Brittleness of Handwritten Digit Recognition Models, Alexander K. Seewald, 30 Nov 2011
- [4] A Novel Handwritten Digit Classification System Based on Convolutional Neural Network Approach, Ali Abdullah Yahya, 18 September 2021
- [5] Handwritten Digit Recognition Using Machine Learning Algorithms, S. M. Shamim, Md Badrul Alam Miah, Angona Sarker, Masud Rana, Abdullah Al Jobair, March 2018
- [6]. Handwritten digit recognition using deep learning, International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), vol. 6, no. 7, A. Dutta and A. Dutta, July 2017.

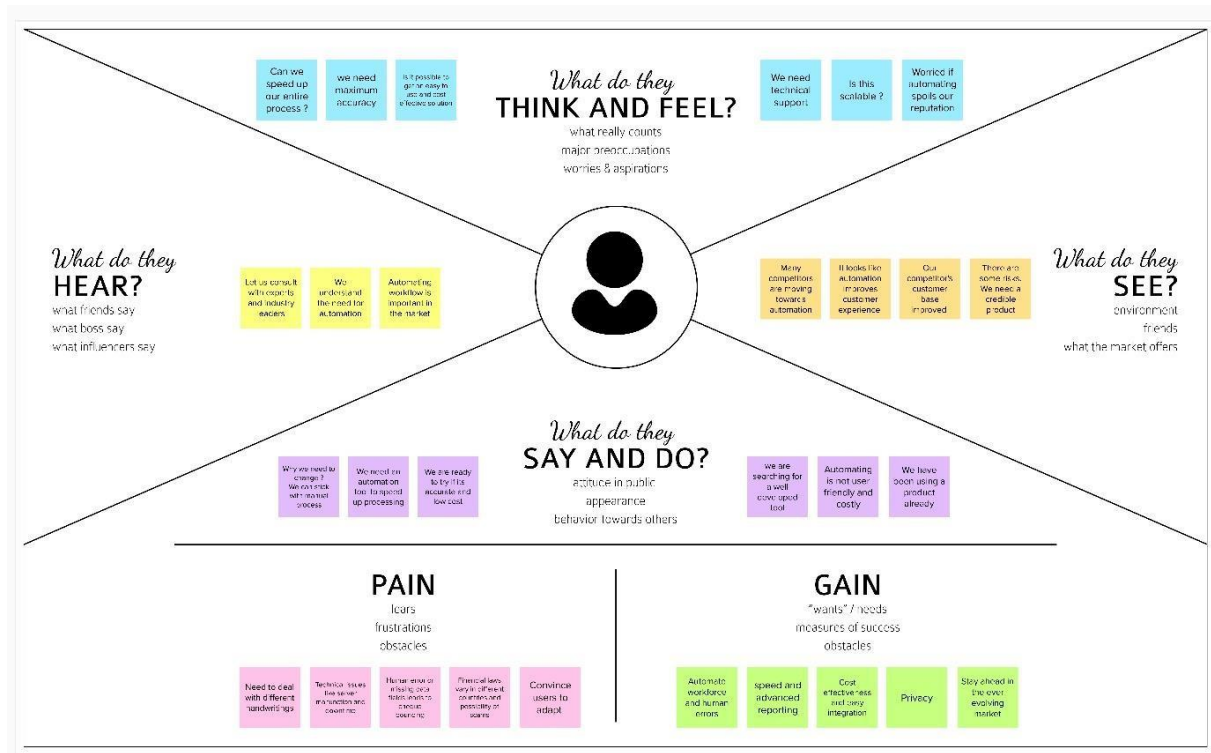
- [7]. Automatic prediction of age, gender, and nationality in offline handwriting. EURASIP Journal on Image and Video Processing, no. 1, Al Maadeed, Somaya, and Abdelaali Hassaine, 2014.
- [8]. Handwritten Digits Recognition, Project Report, Gaurav Jain, Jason Ko, University of Toronto, 11/21/2008.
- [9]. Handwritten recognition using SVM, KNN and neural network, arXiv preprint arXiv:1702.00723. Hamid, Norhidayu Abdul, and Nilam Nur Amir Sjarif, 2017.
- [10]. Digit Classification using the MNIST Dataset, M. Wu and Z. Zhang, Handwritten, 2010.
- [11]. Handwritten digit classification using support vector machines, R.G. Mihalyi, 2011.

2.3. PROBLEM STATEMENT DEFINITION

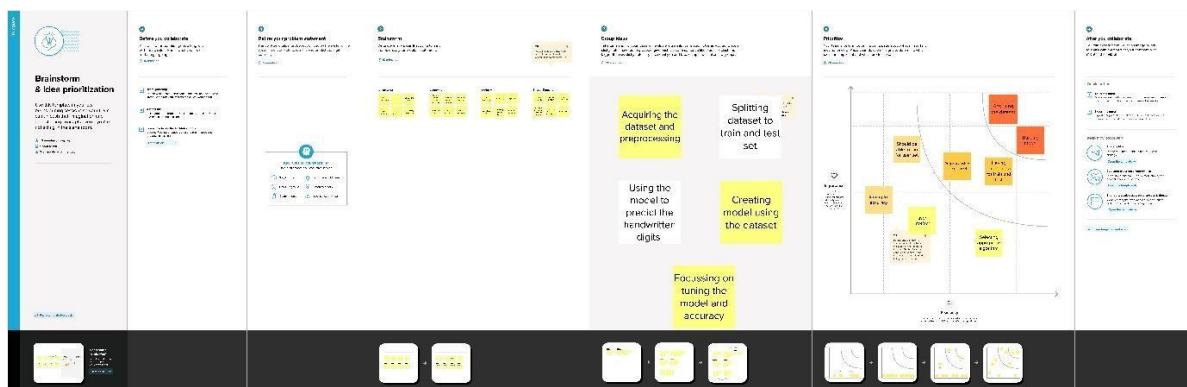
Handwriting recognition is one of the compelling research works going on because every individual in this world has their own style of writing. Since the style of handwriting changes with every individual, it is a challenging task in identifying the characters correctly. The thickness of stroke, style carries uniqueness with different person depending on them. It is the capability of the computer to identify and understand handwritten digits or characters automatically. Because of the progress in the field of science and technology, everything is being digitalized to reduce human effort. Hence, there comes a need for handwritten digit recognition in many real-time applications. MNIST data set is widely used for this recognition process and it has 70000 handwritten digits. Artificial neural network is used to train these images and build a deep learning model. The Convolutional Neural Networks (CNN) is a deep learning algorithm that is highly suitable for image recognition and those tasks involving processing of pixel data. Convolutional neural networks (CNNs) are very effective in perceiving the structure of handwritten characters/words in ways that help in automatic extraction of distinct features and make CNN the most suitable approach for solving handwriting recognition problems. Our aim in the proposed work is to deploy the CNN model effectively and produce a good result with better accuracy. The main objective was to actualize a pattern characterization method to perceive the handwritten digits provided in the MNIST data set of images of handwritten digits (0-9). Web application is created where the user can upload an image of a handwritten digit. This image is analysed by the model and the detected result is returned on to UI.

3. IDEATION AND PROPOSED SOLUTION

3.1. EMPATHY MAP CANVAS



3.2. IDEATION AND BRAINSTORMING



3.3. PROPOSED SOLUTION

S. No	Parameter	Description
1.	Problem Statement	To develop a system that will identify the handwritten digit correctly
2.	Idea / Solution Description	<ul style="list-style-type: none"> a. Predict the digit using deep learning algorithms b. Ensure the correct prediction of digit
3.	Novelty / Uniqueness	<ul style="list-style-type: none"> a. Predict the digits instantly b. Recognizing digits irrespective of the varying handwriting styles
4.	Social impact / Customer Satisfaction	Serves workers at postal offices and bank, where it can be used for mail sorting and check processing. Also helpful in data form entry. It will reduce the work load from workers and hence reduce stress
5.	Business Model	<ul style="list-style-type: none"> a. Collaboration with postal office and banks. And other corporations using database b. Saves time and cost with manual labor c. Bank check programming d. Tax documentation
6.	Scalability of the Solution	<ul style="list-style-type: none"> a. Fine tuning the model aiming to produce more accurate results b. Making it independent with less human intervention

3.4. PROBLEM SOLUTION FIT

Project Title: A novel method for Handwritten Digit Recognition

Project Design Phase-I - Solution Fit

Team ID: PNT2022TMD28868

Define CS, fit into CC	1. CUSTOMER SEGMENT(S) CS People working with postal office sorting mails and huge data processing	6. CUSTOMER CONSTRAINTS CC Takes up lot of time from manual side and it costs to hire human resources	5. AVAILABLE SOLUTIONS AS Hiring more labour to work through huge data like sorting through mails with postal code.	Explore AS, differentiate
	2. JOBS-TO-BE-DONE / PROBLEMS J&P To make it possible for the machine to identify the handwritten digit correctly	9. PROBLEM ROOT CAUSE RC It is exhausting to sort through piles of records and documents which becomes bothersome. It takes huge amount of time and money while using manual labour	7. BEHAVIOUR BE They hire more hands to deal with excess data and records	
Focus on J&P, tap into BE, understand RC	3. TRIGGERS TR Due to huge consumption of time and wastage of manual resources	10. YOUR SOLUTION SL Develop a artificially intelligent machine that can perform the classification of handwritten digits with best accuracy attainable to assist manual force.	8. CHANNELS of BEHAVIOUR CH 8.1. The user can make a real time recognition of digits using the model 8.2. The user using the system can take breaks and save time just guiding the machine. Efforts are reduced significantly on manual side.	Identify strong TR & EM
	4. EMOTIONS: BEFORE / AFTER EM They feel exhausted and it easily gets tiresome to swift through data all day. It also leads to stress and irritation.			

4.0. REQUIREMENT ANALYSIS

4.1. FUNCTIONAL REQUIREMENTS

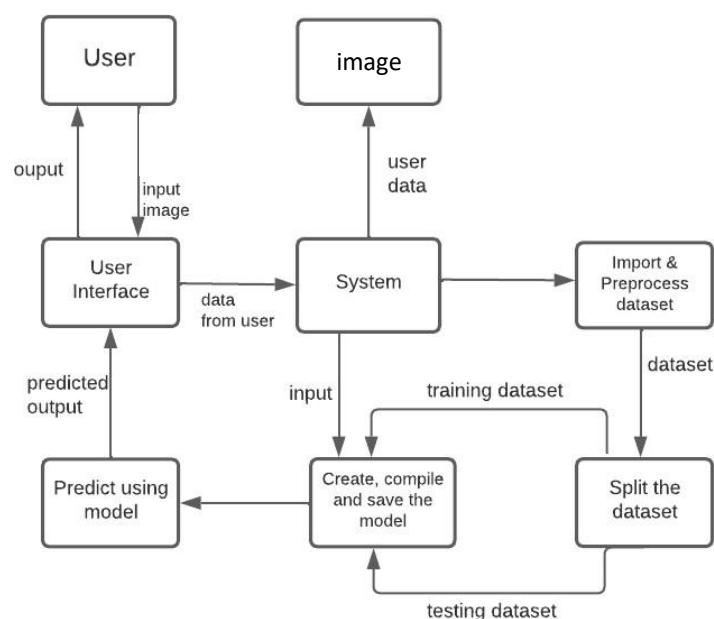
FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form Registration through Gmail Registration through LinkedIn
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-3	Login	Login using credentials
FR-4	Upload Input	Upload image Upload via on-screen
FR-5	Train	Multiple inputs to train
FR-6	Test	Test via fresh data
FR-7	Maintenance	Handle all user data
FR-8	Update	Update if any new feature available

4.2. NON-FUNCTIONAL REQUIREMENTS

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	It will be easily accessible by the user. Simple and easy to understand
NFR-2	Security	The data and input given by the user will be protected. Password-protected and only the particular user can alter their data
NFR-3	Reliability	It is highly reliable and the accuracy can be increased with training
NFR-4	Performance	Good performance with short time to run
NFR-5	Availability	It is easily available on all platforms. Available on web
NFR-6	Scalability	It is scalable and new features can be integrated. Multiple digits can be recognised at a time, real time recognition can be done

5. PROJECT DESIGN

5.1. DATA FLOW DIAGRAM



1. User Interface
2. Input from the user
3. System loads the dataset
4. Splitting into training and testing
5. CNN modelling
6. Output prediction
7. Display the output

5.2. SOLUTION AND TECHNICAL ARCHITECTURE

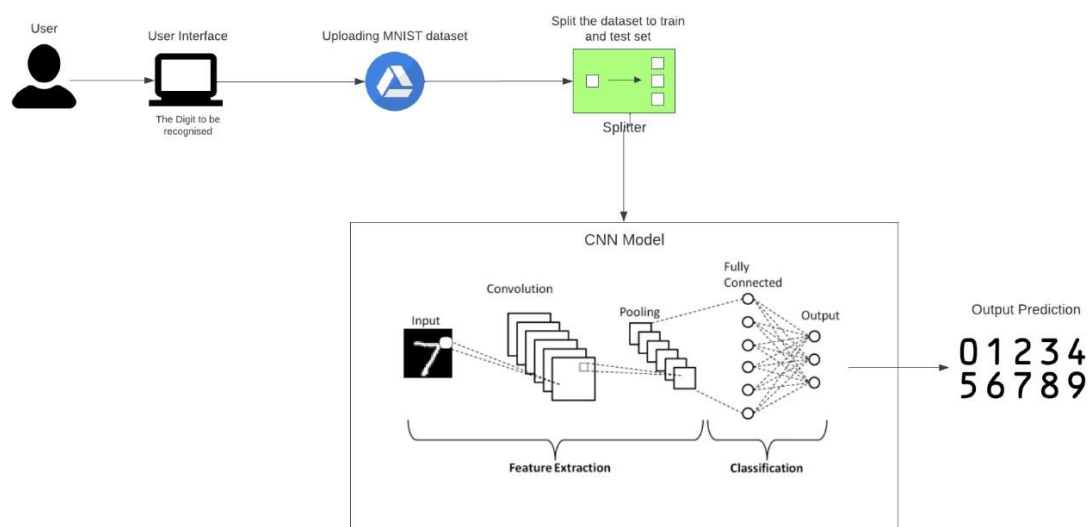
Solution Architecture

Handwritten Digit Recognition can be done with the help of the deep learning algorithm, Convolutional Neural Network (CNN) which works similar to that of the neurons in human brain. The MNIST dataset containing 70,000 images of handwritten digits is loaded and pre-processed. The dataset is split as training and testing set and then the CNN model is created and saved. The model is used for identifying the handwritten digit from the user.

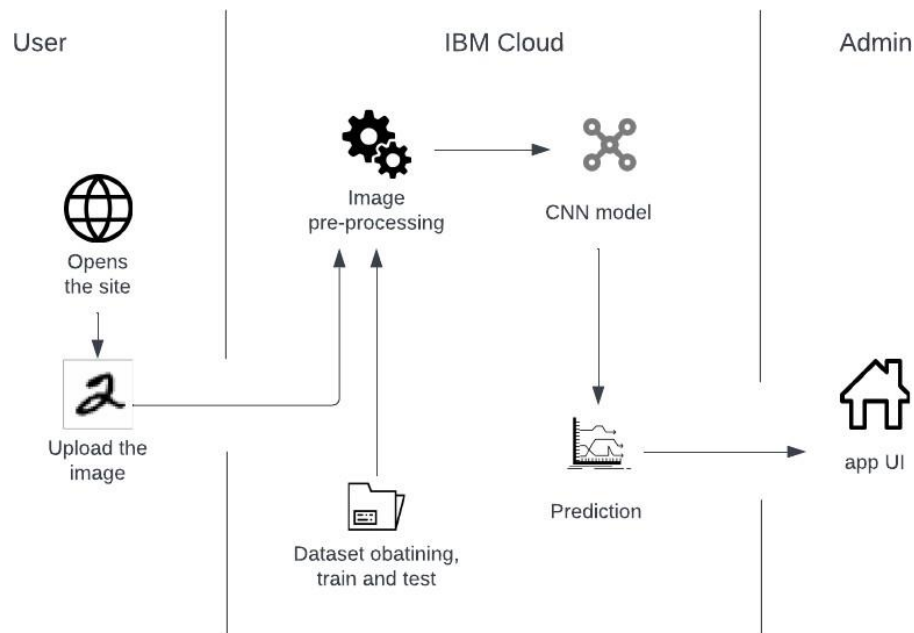
The major steps involved in this.

1. Load the dataset
2. Splitting into training and testing
3. CNN modelling
 - 3.1. Convolution
 - 3.2. Pooling
 - 3.3. Fully connected
4. Output prediction

Architecture Diagram



Technical architecture



Components & Technologies:

S.No	Component	Description	Technology
1.	User Interface	Open the Web UI	HTML, CSS, JavaScript
2.	Application Logic-1	To download and process data	Python
3.	Application Logic-2	To train and deploy the model	IBM Watson ML service
4.	Database	User data and inputs	MySQL, NoSQL, etc.
5.	Cloud Database	Database Service on Cloud to store all the data	IBM DB2, IBM Cloudant etc.
6.	File Storage	To store user data and the input digit images	IBM Block Storage or Other Storage Service or Local Filesystem
7.	Machine Learning Model	Model to recognise the handwritten digits	Image Recognition Model

S.No	Component	Description	Technology
8.	Infrastructure (Server / Cloud)	Application Deployment on Local System / Cloud Local Server Configuration: Cloud Server Configuration	Local, Cloud Foundry, Kubernetes, etc.

Application Characteristics:

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	The handwritten digit dataset	MNIST dataset
2.	Security Implementations	Only authorized user can access the data, users are authenticated with passwords	SHA-256, Encryptions, IAM Controls, OWASP etc.
3.	Scalable Architecture	The model is highly scalable to see performance changes with design change	3-tier architecture
4.	Availability	The system will be available for the users when it is requested handling traffic well	Distributed servers
5.	Performance	The response time is small and user gets their request executed in seconds	Cache

5.3. USER STORIES

USER TYPE	FUNCTIONAL REQUIREMENT (EPIC)	USER STORY NUMBER	USER STORY/TASK	ACCEPTANCE CRITERIA	PRIORITY	RELEASE
Customer	Registration	USN1	I should register with my credentials like username, email and passwords as a customer	I can access my account via email	High	Sprint-1
	Verification	USN2	As a customer I will verify my registration with email received	I can verify my registration through my email	High	Sprint-1
	Login	USN3	I, as a customer, should login with my credentials	I can login the page	Low	Sprint-2
	Upload Input	USN4	I will upload my input as an image or via on -screen mode	I can write the digit or upload the image	High	Sprint-2
	Train	USN5	As a customer I will train the system thoroughly with proper and frequent inputs	I can upload proper images frequently to train the system	Medium	Sprint-3
	Test	USN6	As a customer I will test the system periodically with new data to check the system accuracy	I can check the system accuracy with my fresh data	High	Sprint-3
Administrator	Maintenance	USN7	As an admin I will maintain the user data properly	I can handle the customer data	High	Sprint-4
	Update	USN8	As an administrator I will check if I can make any effective updates on the system	I will update the system when it is required	Medium	Sprint-4

6. PROJECT PLANNING & SCHEDULING

6.1. SPRINT PLANNING AND ESTIMATION

RELEASE	FUNCTIONAL REQUIREMENT (EPIC)	USER STORY NUMBER	USER STORY/TASK	PRIORITY	STORY POINTS	TEAM MEMBERS
Sprint-1	Registration	USN1	I should register with my credentials like username, email and passwords as a customer	High	2	Mohan B, Sakthivel G
Sprint-1	Verification	USN2	As a customer I will verify my registration with email received	High	2	Abilash R, Pragadeeswaran J, Sakthivel G
Sprint-2	Login	USN3	I, as a customer, should login with my credentials	Low	1	Mohan B, Abilash R
Sprint-2	Upload Input	USN4	I will upload my input as an image or via on -screen mode	High	1	Pragadeeswaran J, Sakthivel G
Sprint-3	Train	USN5	As a customer I will train the system thoroughly with proper and frequent inputs	Medium	3	Abilash R, Pragadeeswaran J, Sakthivel G, Mohan B
Sprint-3	Test	USN6	As a customer I will test the system periodically with new data to check the system accuracy	High	3	Abilash R, Pragadeeswaran J, Sakthivel G, Mohan B
Sprint-4	Maintenance	USN7	As an admin I will maintain the user data properly	High	2	Abilash R, Pragadeeswaran J, Sakthivel G, Mohan B
Sprint-4	Update	USN8	As an administrator I will check if I can make any effective updates on the system	Medium	3	Abilash R, Pragadeeswaran J, Sakthivel G

6.2. SPRINT DELIVERY SCHEDULE

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	31 Oct 2022	20	31 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	5 Nov 2022	20	5 Nov 2022
Sprint-3	20	6 Days	5 Nov 2022	12 Nov 2022	20	12 Nov 2022
Sprint-4	20	6 Days	12 Nov 2022	19 Nov 2022	20	19 Nov 2022

6.3. REPORTS FROM JIRA

Velocity:

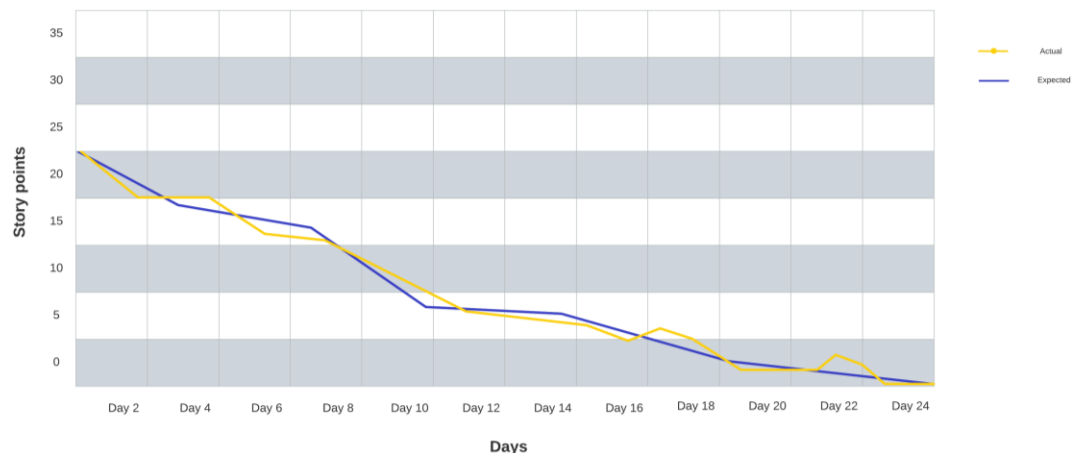
Imagine we have a 6-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

$$AV = \text{sprint duration} / \text{velocity}$$

$$AV = 20/6 = 3.33$$

Burndown Chart:

A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies such as Scrum. However, burn down charts can be applied to any project containing measurable progress over time.



7. CODING AND SOLUTIONING

7.1. FEATURE-1 MODEL BUILDING

ML depends heavily on data, without data, it is impossible for a machine to learn. It is the most crucial aspect that makes algorithm training possible. In Machine Learning projects, we need a training data set. It is the actual data set used to train the model for performing various actions. TensorFlow already has MNIST Data set so there is no need to explicitly download or create Dataset. The MNSIT dataset contains ten classes: Digits from 0-9. Each digit is taken as a class. The required libraries are imported which are required for the model to run. The dataset for this model is imported from the Keras module. The data is split into train and test. Using the training dataset, the model is trained and the testing dataset is used to predict the results. Basically, the pixel values range from 0-255. The value of each image is stored is y_train. The model is built with convolutional, pooling and dense layers. The created model is then compiled and saved.

7.2. FEATURE-2 WEB APPLICATION

HTML, CSS and JavaScript are used to create the web pages for the front end. An html page that takes in image files as input using form and submits to back end is created. A flask app is created using python flask, where it receives the image files from the templates, html pages and the prediction operation is done over this image. Later the predicted output is sent to the result page.

8 TESTING

8.1 TEST CASES

Test case ID	Feature Type	Component	Test Scenario	Pre-Requisite	Steps To Execute	Expected Result	Actual Result	Status	Comments	TC for Automation(Y/N)
HomePage_TC_001	Functional	Home Page	Verify user is able to see the navigation bar on top		1.Enter URL and click go 2.Click on the Recognise button on navigation bar	Move to recognise page	Working as expected	Pass		Y
RecognizePage_TC_002	Functional	RecognizePage	Verify user is able to move to recognise page		1.Enter URL and click go 2.Click on the Recognise button on navigation bar 3.Click on select file button on the view page	1.user should be navigate to our computer image folder.	Working as expected	pass		Y
RecognizePage_TC_003	Functional	RecognizePage	Verify user is moved to predict page.		1.Enter URL and click go 2.Click on the Recognise button on navigation bar 3.click on select file button on the view page. 4.click on the recognise button.	1.move to predict page.	Working as expected	Pass		N
PredictPage_TC_004	Non-Functional	PredictPage	Verify whether digit is predicted correctly.		1.Enter URL and click go 2.Click on the Recognise button on the navigaor bar 3.click on select file button on the view page 4.Choose on image as you want to predict. 5.Click on recognise button	1.User expects the image to be predicted correctly.	There are incorrect predictions at times	Fail	The accuracy of the system affects the results	N
BackPage_TC_005	Functional	BackPage	In case of incorrect prediction or user wants another image predicted, then user clicks on back button.		1.Enter URL and click go 2.Click on the Recognise button on the navigaor bar 3.click on select file button on the view page 4.Choose on image as you want to predict. 5.click on recognise Button. 6.click on Back Button.	1.user is moved back to recognise page	Working as expected	Pass		Y

8.2 USER ACCEPTANCE TEST

Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	13	2	1	2	18
Duplicate	4	0	1	0	5
External	3	2	1	0	6
Fixed	12	3	2	15	32
Not Reproduced	0	2	0	0	2
Skipped	0	0	2	1	3
Won't Fix	0	3	3	1	7
Totals	32	11	13	20	75

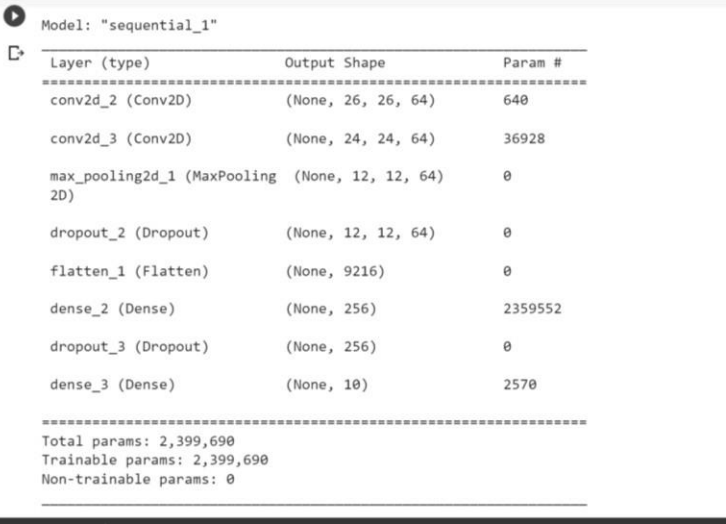
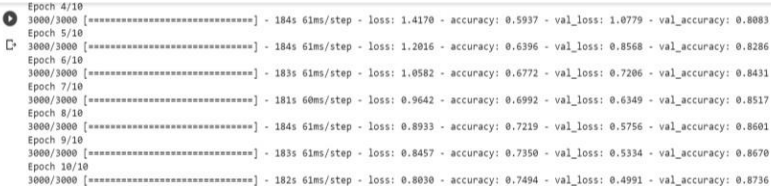
Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	Fail	Pass
Client Application	37	0	0	37
Image	14	0	0	14
Prediction	5	0	2	3
Section	Total Cases	Not Tested	Fail	Pass
Exception Reporting	7	0	0	7
Final Report Output	4	0	0	4
Version Control	2	0	0	2

9. RESULTS

9.1 PERFORMANCE METRICS

S.No.	Parameter	Values	Screenshot
1.	Model Summary		 <p>The screenshot shows the Keras Model Summary for a model named 'sequential_1'. It lists the layers, their output shapes, and the number of parameters. The layers are: conv2d_2 (Conv2D), conv2d_3 (Conv2D), max_pooling2d_1 (MaxPooling 2D), dropout_2 (Dropout), flatten_1 (Flatten), dense_2 (Dense), dropout_3 (Dropout), and dense_3 (Dense). The total number of parameters is 2,399,690, with 2,399,690 trainable parameters and 0 non-trainable parameters.</p>
2.	Accuracy	<p>Training Accuracy – 74.94</p> <p>Validation Accuracy - 87.23000</p>	 <p>The screenshot shows the Keras training and validation accuracy over 10 epochs. The training accuracy starts at 74.94% and increases to 87.23% by epoch 10. The validation accuracy starts at 87.23% and increases to 87.23% by epoch 10. The loss decreases from 1.4170 to 0.8030 over the 10 epochs.</p>

10. ADVANTAGES & DISADVANTEGES

ADVANTAGES:

- It saves times for arranging and sorting huge amount of data
- Only requires far less physical space than the storage of the physical copies.
- Recognising multiple digits on a single frame using sequential model in Keras.
- Data storage, for an example, there are many files, contracts and some personal records that contains some handwritten digits.
- It reduces human effort and labour cost
- This can be used for sorting through mail by postal code

DISADVANTAGES

- The system build is complex and holds difficulty

- The handwriting of every individual varies which proves to be a challenge for the system to predict
- Possible unemployment of labour that is typical of technology growth
- The accuracy is not guaranteed and there are risk of errors

11. CONCLUSION

Handwritten digit recognition has immense applications in the field of medical, banking, student management, and taxation process etc. Many classifiers like KNN, SVM, and CNN are used to identify the digit from the handwritten image. Here we've used CNN for implementation. Convolutional Neural Network gets trained from the real-time data and makes the model very simple by reducing the number of variables and gives relevant accuracy. MNIST dataset consist of handwritten numbers from 0-9 and it is a standard dataset used to find performance of classifiers.

Results of HDR is improved a lot by using CNN classifier but it can be improved further in terms of complexity, duration of execution and accuracy of results by making combination of classifiers or using some additional algorithm with it. More accurate results can be established with more convolution layers and more number of hidden neurons. It can completely abolish the need for typing. Digit recognition is an excellent prototype problem for learning about neural networks and it gives a great way to develop more advanced techniques of deep learning.

12. FUTURE SCOPE

In future, different architectures of CNN, namely, hybrid CNN, viz., CNN-RNN and CNN-HMM models, and domain-specific recognition systems, can be investigated. Evolutionary algorithms can be explored for optimizing CNN learning parameters, namely, the number of layers, learning rate and kernel sizes of convolutional filters. The 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. In future, the application of these algorithms lies from the public to high-level authorities, as from the differentiation of the algorithms above and with future development we can attain high-level functioning applications which can be used in the classified or government agencies as well as for the common people. Currently only the digits are recognized. In future the all the characters in all the language can be predicted with high accuracy rate.

13. APPENDIX

Source code

The necessary libraries are imported.

```
import keras
import tensorflow
from keras.datasets import mnist
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
from tensorflow.keras.optimizers import SGD
```

The MNIST dataset is downloaded from the keras library and the data is analyzed.

```
# the data, split between train and test sets
(x_train,y_train),(x_test,y_test)=mnist.load_data()
print(x_train.shape,y_train.shape)
print(x_test.shape,y_test.shape)
x_train[0]
```

The data is pre-processed and reshaped

```
#Preprocess the data
num_classes=10
x_train=x_train.reshape(x_train.shape[0],28,28,1)
x_test=x_test.reshape(x_test.shape[0],28,28,1)
input_shape = (28,28,1)
```

Applying one-hot encoding. The class vectors are converted to binary class matrices.

```
#Convert class vectors to binary class matrices
y_train=keras.utils.to_categorical(y_train,num_classes)
y_test=keras.utils.to_categorical(y_test,num_classes)
x_train=x_train.astype('float32')
x_test=x_test.astype('float32')
x_train=x_train/255
x_test=x_test/255
```

```
print('x_train shape:',x_train.shape)
print(x_train.shape[0],'train samples')
```

The CNN model is created. The activation function is Rectified linear unit(ReLU). The pooling layers, dense layers are added and flattened.

```
#Create the Model
batch_size=128
num_classes=10
epochs=20
model = Sequential()
model.add(Conv2D(32,
kernel_size=(3,3),activation='relu',input_shape=input_shape))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(64,activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes,activation='softmax'))
```

The model is then compiled

```
model.compile(loss=keras.losses.categorical_crossentropy,
optimizer=keras.optimizers.
Adadelta(),metrics=['accuracy'])
```

The model is trained

```
hist = model.fit(x_train,
y_train,batch_size=20,epochs=5,verbose=1,validation_data=(x_test, y_test))
```

Observing the metrics and testing the model

```
metrics = model.evaluate(x_test, y_test, verbose=0)
print("Metrics(Loss and Accuracy):")
print(metrics)
prediction = model.predict(x_test[:4])
print(prediction)
```

The model is saved and then tested. A sample image is given in to test the saved model. The image is reshaped and then predicted.

```
model.save('digit_classifier.h5')
from keras.utils.image_utils import img_to_array
from tensorflow.keras.models import load_model
```

```

model = load_model('/content/digit_classifier.h5')
from PIL import Image
import numpy as np

img = Image.open('/content/sample.png').convert("L")
img = img.resize((28,28))
im2arr = np.array(img)
im2arr = im2arr.reshape(1,28,28,1)

#display the image
import matplotlib.pyplot as plt
plt.imshow(img)

#predict the image
y_predict = model.predict(im2arr)
print(np.argmax(y_predict[0]))

```

The pages to display the home and recognise page with navigation bar.

front end.html

```

<html>
  <head>
    <style>
      body {
        background-image: url('file:///C:/Users/BABY%20DEVIL/Desktop/4k-blue-
digits-background-artwork-numbers-digits-textures.jpg');
        margin: 0;
        padding: 0;
        font-family: 'Times New Roman', Times, serif, Helvetica, sans-serif;
      }

      .topnav {
        overflow: hidden;

        padding: 5px;
        background: rgba(255, 255, 255, .7);
        border-radius: 0px 0px 10px 10px;
        margin: 0;

        color: black;
        font-size: large;
        -webkit-backdrop-filter: blur(20px);
        backdrop-filter: blur(10px);
      }

```

```

.topnav a {
    float: left;
    margin: 3px;
    border-radius: 10px;
    color: #480557;
    text-align: center;
    padding: 10px;
    text-decoration: none;
    font-size: 17px;
}

.topnav a:hover {
    background-color: rgb(57, 55, 55);
    border-radius: 10px;
    color: rgb(250, 248, 248);
}

.topnav a.active {
    background-color: rgb(57, 55, 55);
    border-radius: 10px;
    color: rgb(250, 248, 248);
}

.head{
    text-align: center;
    padding: 2rem;
    background: rgba(255, 255, 255, .7);
    border-radius: 20px;
    margin-left: 25%;
    margin-right: 25%;
    margin-top: 5%;
    font-family: 'Times New Roman', Times, serif;
    color: black;
    font-size: large;
    -webkit-backdrop-filter: blur(20px);
    backdrop-filter: blur(10px);
}

.para{
    text-align: center;
    position: absolute;
    width: 400px;
    height: auto;
    padding: 2rem;
    margin-top: 5%;
    margin-left: 30%;
    margin-right: 50%;
    border-radius: 20px;
    background: rgba(255, 255, 255, .7);
    -webkit-backdrop-filter: blur(20px);
    backdrop-filter: blur(10px);
}

```

```

    }
    </style>
</head>
<body>

    <div class="topnav">
        <a class="active" href="#home">Home</a>
        <a class="reg" href="recognise.html">Recognise</a>
    </div>

    <div class="head">
        <p class="txt" style="font-size:larger" >Handwritten Digit Recognition
        </p>
        <p>Handwritten digit recognition is the ability of machines to recognise the digits
written by human. It is the capability of the computer to identify and understand handwritten
digits or characters automatically. Everything is being digitalized to reduce human effort.
Hence, there comes a need for handwritten digit recognition in many real-time applications.
MNIST data set is widely used for this recognition process and it has 70000 handwritten
digits. We use Artificial neural networks to train these images and build a deep learning
model. Web application is created where the user can upload an image of a handwritten digit.
The uploaded image is analyzed by deep learning model and predict the correct digit with high
accuracy and the predicted digit returned as output.
        </p></div>
    </body>
</html>

```

The recognise page where the user can upload the image for prediction
recognise.html

```

<html>
  <head>
    <title>Digit Recognition</title>
    <style>
      body {
        background-image: url('file:///C:/Users/BABY%20DEVIL/Desktop/white-elegant-
texture-background-style_23-2148432200.webp');
        margin: 0;
        font-family: 'Times New Roman', Times, serif, Helvetica, sans-serif;
        height: 100%;
        width: 100%;
      }
      h1 {
        display: block;
        font-size: 3.5em;
        margin-top: 5.4em;
        margin-bottom: 0em;
        margin-left: 50%;
      }
    </style>
  </head>
  <body>
    <div class="topnav">
      <a class="active" href="#home">Home</a>
      <a class="reg" href="recognise.html">Recognise</a>
    </div>
    <div class="head">
      <p class="txt" style="font-size:larger" >Handwritten Digit Recognition
      </p>
      <p>Handwritten digit recognition is the ability of machines to recognise the digits
written by human. It is the capability of the computer to identify and understand handwritten
digits or characters automatically. Everything is being digitalized to reduce human effort.
Hence, there comes a need for handwritten digit recognition in many real-time applications.
MNIST data set is widely used for this recognition process and it has 70000 handwritten
digits. We use Artificial neural networks to train these images and build a deep learning
model. Web application is created where the user can upload an image of a handwritten digit.
The uploaded image is analyzed by deep learning model and predict the correct digit with high
accuracy and the predicted digit returned as output.
      </p></div>
    </body>
  </html>

```



```

        margin-right: 0;
        font-weight: bold;
    }
.button {
    border:#e5b9f3;
    color: rgb(56, 1, 69);
    padding: 15px 32px;
    text-align: center;
    text-decoration: none;
    display: inline-block;
    font-size: 16px;
    margin: 4px 2px;
    cursor: pointer;
}

.button1 {
    background-color: #b6e6f0;
    margin-top: 5.4em;
    margin-left: 56%;
    margin-right: 0;
    border: black;
}
.button2 {
    background-color: #b6e6f0;
    margin-top: 5.5em;
    margin-left: 55%;
    margin-right: 0;
    border: black;
}
</style>
<script>
    function preview() {
        frame.src=URL.createObjectURL(event.target.files[0]);
    }

    $(document).ready(function() {
        $('#clear_button').on('click', function() {
            $('#image').val('');
            $('#frame').attr('src','');
        });
    });
    var input = document.getElementById('image');
    var infoArea = document.getElementById('frame');

    input.addEventListener('change', showFileName);

    function showFileName(event) {
        var input = event.srcElement;
        var fileName = input.files[0].name;

```

```

        infoArea.textContent = 'File name: ' + fileName;
    }

</script>
<script src="https://kit.fontawesome.com/b3aed9cb07.js"
crossorigin="anonymous"></script>
<script src="https://code.jquery.com/jquery-3.3.1.slim.min.js" integrity="sha384-
q8i/X+965Dz00rT7abK41JStQIAqVgRVzpbzo5smXKp4YfRvH+8abtTE1Pi6jizo"
crossorigin="anonymous"></script>
<script
src="https://cdnjs.cloudflare.com/ajax/libs/popper.js/1.14.7/umd/popper.min.js"
integrity="sha384-U02eT0CpHqdSJQ6hJty5KVphtPhzWj9WO1clHTMGa3JDZwrnQq4sF86dIHNDz0W1"
crossorigin="anonymous"></script>
<script src="https://stackpath.bootstrapcdn.com/bootstrap/4.3.1/js/bootstrap.min.js"
integrity="sha384-JjSmVgyd0p3pXB1rRibZUAYoIIy60rQ6VrjIEaFf/njGzIxFDs4x0xIM+B07jRM"
crossorigin="anonymous"></script>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@latest"></script>

</head>
<body>
    <h1 style = "color: rgb(2, 60, 0)">Digit Recognition
    <br>
    <br>
    <form action="/recognise" method="POST" enctype="multipart/form-data">
    <input id="image" type="file" name="image" accept="image/png, image/jpeg"
onchange="preview()"><br><br>
    <img id="frame" src="" width="100px" height="100px"/>
    </h1>
    <a class="button button2" id="predict_button" href="predict.html">Recognise</a>
    </form>
</body>
</html>

```

The page where the predicted output is displayed

predict.html

```

<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Prediction</title>
</head>

<style>
    body{
        background-image: url('https://img.freepik.com/premium-vector/falling-colorful-messy-
numbers-math-study-concept-with-flying-digits-fascinating-back-school-mathematics-banner-
white-background-falling-numbers-vector-illustration_174187-2929.jpg?w=2000');
    }

```

```

background-repeat: no-repeat;
height: 100%;
width: 100%
}

#pred{
text-align: center;
font-family: 'Times New Roman', Times, serif;
font-size: 40px;
margin: 0 auto;
padding: 3% 5%;
padding-top: 15%;
color: rgb(0, 10, 80);
}

</style>
<body>
    <p id="pred">PREDICTION : {{ num }}</p>
    <p>
        <a href="recognise.html">
            <button data-inline="True" class="button">Back</button>
        </a>
    </p>
</body>
</html>

```

The flask app.py python code to calculate the prediction value from processing the image uploaded by the user

app.py

```

import os

from flask import Flask, render_template, request
from PIL import Image
from werkzeug.utils import secure_filename
import numpy as np
import tensorflow as tf

app = Flask(__name__)

@app.route('/', methods=['GET'])
def index():
    return render_template('recognise.html')

model = tf.keras.models.load_model("digit_classifier.h5")

```

```
@app.route('/predict', methods = ['POST'])
def predict():
    if request.method == 'POST':
        img = Image.open(request.files['file']).convert("L")
        img = img.resize((28,28))
        im2arr = np.array(img)
        im2arr = im2arr.reshape(1,28,28,1)
        y_pred = model.predict(im2arr)

        return render_template('predict.html', num = str(y_pred))

if __name__ == '__main__':
    app.run(host='0.0.0.0', port=8000, debug=True, threaded=True)
```

Github

<https://github.com/IBM-EPBL/IBM-Project-42944-1660711532>