PR0JECT REPORT

A N0VEL METHOD FOR HANDWRITTEN DIGIT RECOGNITION SYSTEM

SUBMITTED BY

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ABSTRACT

Handwritten digit recognition is the ability of a computer system to recognize the handwritten inputs like digits, characters etc. from a wide variety of sources like emails, papers, images, letters etc. This has been a topic of research for decades. Some of the research areas include signature verification, bank check processing, postal address interpretation from envelopes etc. With the humanization of machines, there has been a substantial amount of research and development work that has given a surge to deep learning and machine learning along with artificial intelligence. Handwriting recognition system is the most basic and an important step towards this huge and interesting area of Computer Vision. With time, machines are getting more and more sophisticated, from calculating the basic sums to doing retina recognition they have made our lives more secure and manageable. In this project illustrates handwritten digit recognition with the help of MNIST datasets using Convolution Neural Network (CNN) models. Deep Learning has emerged as a central tool for self-perception problems like understanding images, voice from humans, robots exploring the world. The project aims to implement the concept of Convolution Neural Network which is one of the important architecture of deep learning. Understanding CNN and applying it to the handwritten recognition system, is the major target of the proposed system. The main objective of this project is to the accuracy of the models stated above along with their execution time to get the best possible model for digit recognition.

1. INTRODUCTION

1.1 PROJECT OVERVIEW

The ability of a machine to read and understand handwritten input from many sources, such as paper documents, pictures, touch screen devices, etc., is known as handwriting recognition. A new field of study that has many applications in businesses, offices, and industries is the recognition of handwritten and computerised characters. This project's major goal is to develop an expert system for "Handwritten Digit Recognition using Deep Learning" that can accurately identify a certain character of type format using an artificial neural network technique. Neuronal computing is still an emerging discipline, hence its design elements are less clearly defined than those of other architectures. Data parallelism is implemented via neural computers. The manner that neural computers are operated is entirely different from the way that conventional computers are operated. This application can recognise any character (or digit) that is provided in the input image. When a character input image is provided to the proposed system, it will recognise the input character that is provided in the image. Neural networks are used for character recognition and classification. The primary goal of this project is to use an Artificial Neural Network approach to efficiently identify a certain character of type format. Extracting text from photographs or scanned documents is the focus of the image processing section of optical character recognition (OCR). We have decided to concentrate on identifying handwritten digits found in the MNIST database for this project. The objective in this research is to employ straightforward Image Correlation, also known as Matrix Matching, approaches to increase the handwritten digits recognizer's accuracy while avoiding using more complex methods like machine learning.

1.2 PURPOSE

One of the very significant problems in pattern recognition applications is the recognition of handwritten characters. Building an automatic handwritten digit recognition method is the major goal of this project, which will be used to recognise handwritten digit strings. The segmentation of the digits into separate digits is the first step in completing the recognition challenge. The handwritten digit string recognition challenge is then completed by using a digit recognition module to categorise each segmented digit.

2. LITERATURE REVIEW

2.1 EXISTING PROBLEM

2.1.1 TITLE: Handwritten Digit Recognition Using Bayesian ResNet

AUTHOR: Purva Mhasakar, Srimanta

The difficulty of handwritten digit recognition has undergone a number of recent improvements, particularly in the field of neural networks. The neural network-based techniques produce deterministic outputs, making them extremely useful for the kinds of data that have been seen. However, even for classes of data that have not been seen before, these approaches frequently perform similarly. When tested on digits from other languages, a neural network trained on English language digits will still provide a deterministic forecast. Therefore, in this situation, it is necessary to forecast uncertainty for such methods. In order to highlight uncertainty for handwritten digit identification when there is a new class of test digit, we integrate Bayesian inference into the current ResNet18 framework in this research. The new architecture is known as B-ResNet. Given that India is a relatively linguistically diverse nation, the challenge of handwritten digit recognition is made more difficult in cases involving Indian languages. On Indian scripts, a great deal of research has been conducted, which will be covered in more detail in the part that follows. Due to the co-occurrence of variation and resemblance among many scripts, the issue is complicated. We suggest a B-ResNet architecture in which probability distributions are used in place of point estimates for weights. This aids in quantifying uncertainty when dealing with unidentified data classes.

2.1.2 TITLE: Multilingual Text & Handwritten Digit Recognitionand Conversion of Regional languages intoUniversal Language Using Neural Networks

AUTHOR: Bhushan Vidhale, Ganesh Khekare

According to character identification techniques, an illustrated identity is equivalent to a character's likeness. A machine's capacity to acquire and recognise handwritten data from multiple sources, such as papers, pictures, tactile touch devices, etc., is known as handwritten human character recognition. The study of handwriting and computer character recognition is a developing topic with several applications in businesses, offices, and banking. The main goal of this research project is to create an informed framework for "Handwritten Character Recognition (HCR) victimisation Neural Network" that can accept specific type-format character victimisation as an alternative Neural Network technique. The optimum way for regulating visuals is the neural method, therefore style components are distributed more thinly than in other systems. In parallel, neural computers produce results. Neural computers operate in a way that is completely different from conventional operation. Neural computers are trained (not programmed) in such a way that how it is supplied in a clear beginning state (data input); they either assign the information (input file or computer file) into one of the many categories or let the initial data to develop to maximise a clear intriguing attribute. In this study, a character recognition model in Matlab and a machine learning model for recognising handwritten digits are both used. The study of pattern recognition and machine learning has given handwriting recognition a specific place because of its vast applications. When it's challenging for the viewer to read someone else's handwriting, this approach provides the answer. Convolutional Neural Networks, a specific kind of deep neural network, are what we're using for this. A GUI is created where we can sketch the digit and instantly recognise it. You must have a foundational understanding of Python programming, deep learning, and a library for creating GUIs in order to complete this Python project.

2.1.3 TITLE: Handwritten Digit Recognition Using Deep Learning

AUTHOR: Gaganashree J. S. Padmashali

Deep learning has recently changed the face of machine learning by giving it a huge artificial intelligence boost thanks to the rise of Artificial Neural Networks (ANN). One of the most well-known challenges in deep learning and computer vision applications is the handwritten digit recognition problem. In pattern recognition applications, handwritten digit recognition is a critical problem. Applications for digit recognition include sorting postal mail, processing checks, filling out forms, etc. The capacity to create an effective algorithm that can recognise handwritten numerals submitted by users via a scanner, tablet, and other digital devices is the key to solving the issue. The method for offline handwritten digit recognition backed by several deep learning techniques is presented in this research. The goal of this study is to ensure efficient and trustworthy methods for handwritten digit recognition. Recognition is the process of setting something or a person apart from previous encounters or knowledge. Recognizing or identifying the digits in any document is known as "digit recognition." A machine's ability to prepare itself or interpret the digits is known as a "digit recognition framework." Handwritten A computer's job in digit recognition is to decipher manually written digits from sources including messages, bank checks, papers, and photos for online handwriting recognition. Recognize licence plates, process bank checks, enter numbers in any format, etc. on the tablet. Numerous methods offered by machine learning can lessen the effort required to recognise handwritten digits. For the following applications—online digit recognition on a tablet computer, reading zip codes from mail, and processing bank check applications—recognizing handwritten digits with the aid of a classifier is especially crucial. Many issues come up when attempting to tackle this issue. Handwritten numbers can vary in size, thickness, direction, and location with respect to the edge.

2.1.4 **TITLE:** Multi-script Handwritten Digit Recognition Using Multi-task Learning

AUTHOR: Mesay Samuel Gondere, Lars Schmidt-Thieme

One of the many areas of machine learning that has been intensively investigated is handwritten digit recognition. There are numerous additional research works on different script recognition in addition to the extensive research on handwritten digit recognition on the MNIST dataset. However, multi-script digit recognition, which promotes the creation of reliable and versatile systems, is not very popular. Working on multi-script digit recognition also makes it possible to learn multiple tasks at once, for example, by thinking of script classification as a related activity. It is clear that using knowledge from related activities to infer new information, multi-task learning enhances model performance. As a result, multi-task learning will be used in this study to examine handwritten digit recognition in many scripts. Amharic handwritten character recognition will also be tested as an example of the problem's resolution in action. In order to demonstrate that multi-task models with reformulation of the separate tasks have produced promising results, the handwritten digits of three scripts, including Latin, Arabic, and Kannada, are analysed. In this study, a unique approach to leveraging predictions from the individual tasks was suggested to aid classification performance and regularise the various losses for the main task. The results of this study are superior to both the baseline and the traditional multi-task learning models. More significantly, it prevented the need to weigh the various task losses, which is one of the difficulties with multi-task learning.

2.1.5 TITLE: Hybrid CNN-SVM Classifier for Handwritten Digit Recognition

AUTHOR: Savita Ahlawata, Amit Choudhary

In order to recognise handwritten digits from the MNIST dataset, this research aims to create a hybrid model using powerful Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The suggested hybrid model integrates both classifiers' salient characteristics. In the proposed hybrid model, SVM serves as a binary classifier and CNN serves as an automatic feature extractor. The algorithm employed in the proposed model is trained and tested using the MNIST dataset of handwritten digits. The handwritten digit pictures in the MNIST dataset are varied and severely warped. With the use of CNN's receptive field, the most distinctive elements of these handwritten numerals may be automatically extracted. With regard to the MNIST handwritten digits dataset, the experimental results show the effectiveness of the suggested framework by achieving a recognition accuracy of 99.28%. In the field of handwriting recognition, handwritten digit recognition is currently a hot topic for research. For practical applications that require high recognition accuracy and reliability, numerous handwritten digit recognition systems have been presented in recent years. The recognition method is made more complex by the characters that have been touched or overlapped as well as by the various handwriting patterns and styles used by different people.

2.2 REFERENCES

1. Purva Mhasakar, Srimanta MandalHandwritten Digit Recognition Using Bayesian ResNet, 2021.
2. Bhushan Vidhale, Ganesh Khekare, Multilingual Text & Handwritten Digit Recognition and Conversion of Regional languages into Universal Language Using Neural Networks, 2021.
3. Gaganashree J. S. Padmashali, Handwritten Digit Recognition Using Deep Learning, 2021.
4. Mesay Samuel Gondere, Lars Schmidt-Thieme, Multi-script Handwritten Digit Recognition Using Multi-task Learning, 2021.
5. Savita Ahlawata, Amit Choudhary, Hybrid CNN-SVM Classifier for Handwritten Digit Recognition, 2020.

2.3 PROBLEM STATEMENT DEFINITION

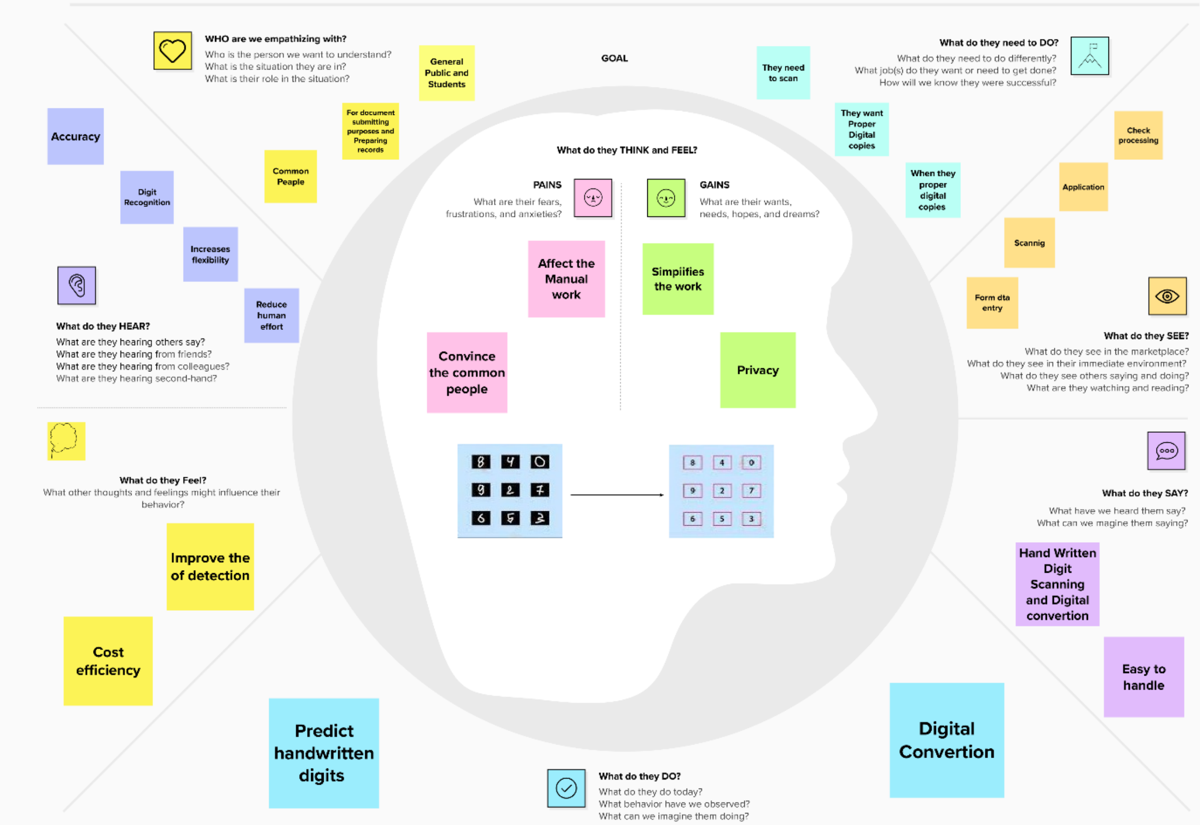
As handwriting varies from person to person, handwritten numbers do not always have the same height, weight, orientation, or marginal justification. The general problem is to distinguish the digits due to the similarity of digits such as 1 and 7, 5 and 6, 3 and 8, 2, five, two and seven. We would like to produce a model that transforms the handwritten digits into a typical type in various types so that no misunderstanding is created. Handwritten digit recognition has recently been of very interest among the researchers because of the evolution of various Machine Learning, Deep Learning and Computer Vision algorithms. The challenge concerning the shape recognition problem such as handwritten character recognition remain in finding features that maximize the interclass variability while minimizing the intra-class variability. Feature extraction methods can be categorized into two classes:

- Structural features, which extract geometrical and topological properties such as the number and position of dots, the presence of loops, the orientation of curves...etc.
- Statistical features, such as histograms of projection profile and transitions, moments, histograms of gray level distribution, Fourier descriptors and chain code...etc

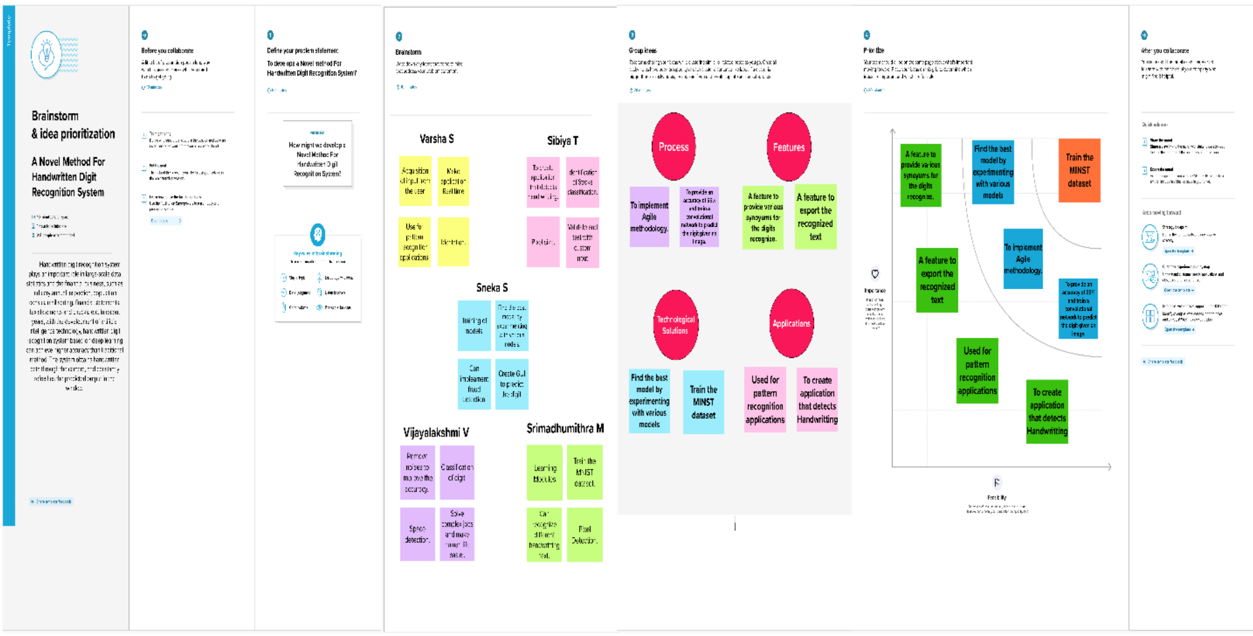
After applying some pre-processing technique and normalizing the image, zoning and crossing counts are combined to represent the feature set. Self-organized map is used to cluster the classes and for creation of binary decision tree. For each node the classifier among SVM, KNN and neural networks who gives the best recognition rate is considered as the main classifier of the node.

3. IDEATION & PROPOSED SOLUTION

3.1 EMPATHY MAP CANVAS



3.2 IDEATION & BRAINSTORMING



3.3 PROPOSED SOLUTION

Handwritten Digit Recognition is a classic problem of image classification. In this, we have to classify handwritten digits into labels i.e. 0-9. Neural Network models are very powerful and efficient classification methods to perform this task. Human beings are intelligent and can read and recognize different handwritten characters and digits written by other fellow humans. We want to inculcate the same features in a machine using Artificial Intelligence and Deep Learning. Training a model for all the different handwritings in this world is impossible as handwriting is unique to every individual. So we can train a model using a large dataset of handwritten digits like the MNIST dataset and test them on other handwritings. OCR is challenging but very useful for quick processing of data records like bank statements, emails, passport documents, invoices, mark sheets, etc. OCR helps in digitizing handwritten and printed text and hence making it easy to apply functions like searching, sorting, and editing easier. Accuracy is the most important parameter in our proposed system - to automate the process of manual entry of numeric data (marks, roll number, subject code, etc.), as even one wrongly recognized digit can have serious consequences. The accuracy and efficiency of the system bank upon the methodology and dataset used. In this implementation, we have used the Convolutional Neural Network (CNN). CNN has a couple of key characteristics. The patterns that they learn are translation invariant. After learning a certain pattern convolution neural network can recognize it anywhere. They can learn spatial hierarchies of the pattern. Accuracy is the most important parameter in our proposed system - to automate the process of manual entry of numeric data (marks, roll number, subject code, etc.), as even one wrongly recognized digit can have serious consequences. The accuracy and efficiency of the system bank upon the methodology and dataset used. In this implementation, we have used the Convolutional Neural Network (CNN). CNN has a couple of key characteristics. The patterns that they learn are translation invariant. After learning a certain pattern convolution neural network can recognize it anywhere. They can learn spatial hierarchies of the pattern.

3.4 PROBLEM SOLUTION FIT

Today, more than ever before, there are many applications for image processing, and a variet y of software programmes have been created that do it. In order to prevent accidents, self-driving cars can now recognise other vehicles and people. Additionally, this technology allow s several social media platforms, including Facebook, to perform facial recognition. The idea of optical character recognition, which we will be exploring in this project, is also used by var ious software programmes to recognise the characters in some photos.The method of extracti ng characters from images is known as optical character recognition and is one of the more sp ecialised areas of image processing (OCR). This technique involves interpreting a scanned te xt of typed characters or an image comprising one or more charac

4. REQUIREMENT ANALYSIS

4.1 FUNCTIONAL REQUIREMENT

IMAGE ACQUISITION

Digit recognition problem is a promising problem in handwriting recognition problem. It is also one of the challenging problems in computer vision and machine learning. It is so called challenging task as developing an accurate automated recognition of handwritten digits is difficult. The applications of digit recognition include bank check processing and online form data submitted by users by using digital devices. The variation in handwriting among people makes it difficult to train the computers to recognize handwritten digits. This work employs machine learning techniques to address the digit recognition problem. To analyse various classification techniques and finding the best technique for digit recognition, the work focuses on utilizing a tool that would embrace multiple types of classification models with diverse performance metrics. In this module, admin can upload the bank statement as trained datasets. This phase can be splited as testing and training. In training phase, each handwritten data can be upload with account details. In testing phase, image can be uploaded with any size and any type

PREPROCESSING

The role of the pre - processing step is it performs various tasks on the input image. It basically upgrades the image by making it reasonable for segmentation. The fundamental motivation behind pre - processing is to take off a fascinating example from the background. For the most part, noise filtering, smoothing and standardization are to be done in this stage. The pre - processing additionally characterizes a smaller portrayal of the example. Binarization changes over a gray scale image into a binary image. The initial approach to the training set images that are to be processed in order to reduce the data, by thresholding them into a binary image. The first step in data pre-processing is data normalization. This is done to apply distance calculations on it

CHARACTER DETECTION

Once the pre - processing of the input images is completed, sub - images of individual digits are formed from the sequence of images. Pre - processed digit images are segmented into a sub - image of individual digits, which are assigned a number to each digit. Each individual digit is resized into pixels. In this step an edge detection technique is being used for segmentation of dataset images. An image of sequence of digit is decomposed into sub images of individual digit. Pre-processed input image is segmented into isolated digit by assigning a number to each digit using a labelling process. After the completion of pre - processing stage and segmentation stage, the pre - processed images are represented in the form of a matrix which contains pixels of the images that are of very large size. In this way it will be valuable to represent the digits in the images which contain the necessary information. This activity is called feature extraction. In the feature extraction stage redundancy from the data is removed. Text strokes are detected using histogram features. Color is measured globally according to the histogram ignoring local neighboring pixels. The histogram-based features used in this work are first order statistics that include mean, variance

HANDWRITTEN RECOGNITION

The Convolutional layer is the core building block of a CNN. The layer's parameters consist of a set of learnable filters (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input and producing a 2- dimensional activation map of that filter. As a result, the network learns filters that activate when they see some specific type of feature at some spatial position in the input.

Feature Extraction: All neurons in a feature share the same weights .In this way all neurons detect the same feature at different positions in the input image. Reduce the number of free parameters.

Subsampling Layer: Subsampling, or down sampling, refers to reducing the overall size of a signal. The subsampling layers reduce the spatial resolution of each feature map. Reduce the effect of noises and shift or distortion invariance is achieved.

Pooling Layer: It is common to periodically insert a Pooling layer in-between successive Conv layer in a ConvNet architecture. Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network, and hence to also control overfitting. The Pooling Layer operates independently on every depth slice of the input and resizes it spatially, using the SOFTMAX operation.

PERFORMANCE EVALUATION

The evaluation of the project can be calculated using accuracy parameterAccuracy can be identified based on true positive rate. The proposed system provide improved accuracy rate. True positive (TP): number of true positives - perfect positive prediction

False positive (FP): number of false positives - imperfect positive prediction

True negative (TN): number of true negatives - perfect negative prediction

False negative (FN): number of true negatives - imperfect negative prediction

Accuracy

Accuracy (ACC) is found as the fraction of total number of perfect predictions to the total number of test data. It can also be represented as 1 – ERR. The finest possible accuracy is 1.0, whereas the very worst is 0.0. The performance of the system shown in table 1 and figure 4.

$$\mathrm{ACC} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FN+FP}} \text{ x } 100$$

The proposed system provide the improved accuracy rate such as 99% in hand digit recognition.

4.2 NON FUNCTIONAL REQUIREMENTS

Usability

The system shall allow the users to access the system with pc using web application. The system uses a web application as an interface. The system is user friendly which makes the system easy

Availability

The system is available 100% for the user and is used 24 hrs a day and 365 days a year. The system shall be operational 24 hours a day and 7 days a week.

Scalability

Scalability is the measure of a system's ability to increase or decrease in performance and cost in response to changes in application and system processing demands.

Security

A security requirement is a statement of needed security functionality that ensures one of many different security properties of software is being satisfied.

Performance

The information is refreshed depending upon whether some updates have occurred or not in the application. The system shall respond to the member in not less than two seconds from the time of the request submittal. The system shall be allowed to take more time when doing large processing jobs. Responses to view information shall take no longer than 5 seconds to appear on the screen.

Reliability

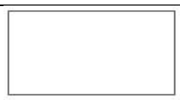
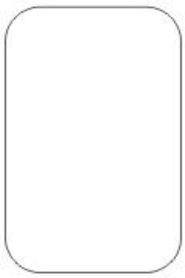
The system has to be 100% reliable due to the importance of data and the damages that can be caused by incorrect or incomplete data. The system will run 7 days a week. 24 hours a day.

5. PROJECT DESIGN

5.1 DATA FLOW DIAGRAMS

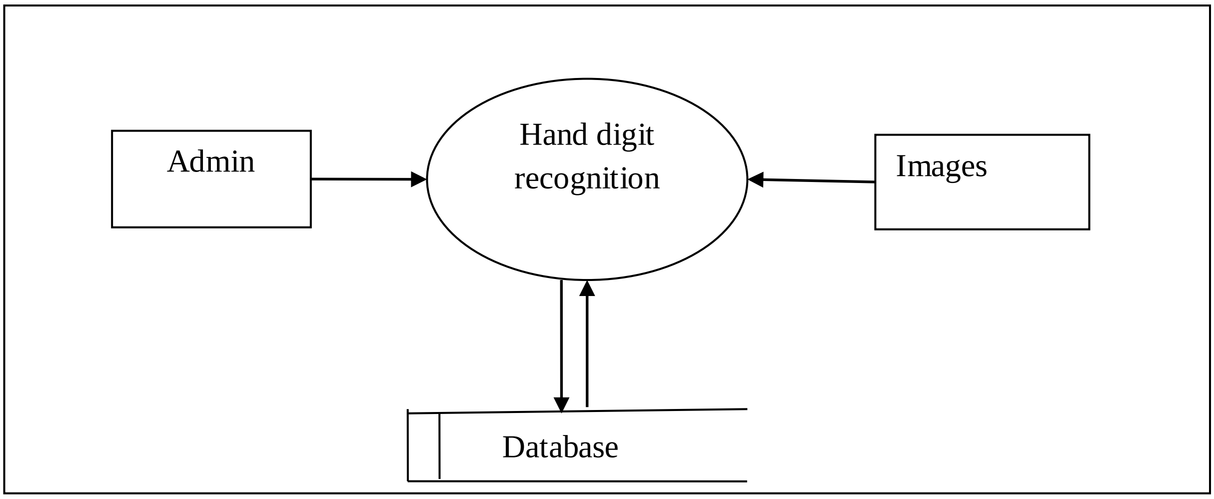
A data flow diagram is a two-dimensional diagram that explains how data is processed and transferred in a system. The graphical depiction identifies each source of data and how it interacts with other data sources to reach a common output. Individuals seeking to draft a data flow diagram must identify external inputs and outputs, determine how the inputs and outputs relate to each other, and explain with graphics how these connections relate and what they result in. This type of diagram helps business development and design teams visualize how data is processed and identify or improve certain aspects.

Data flow Symbols:

Symbol	Description
	An **entity**. A source of data or a destination for data.
	A **process** or task that is performed by the system.
	A **data store**, a place where data is held between processes.
	A **data flow**.

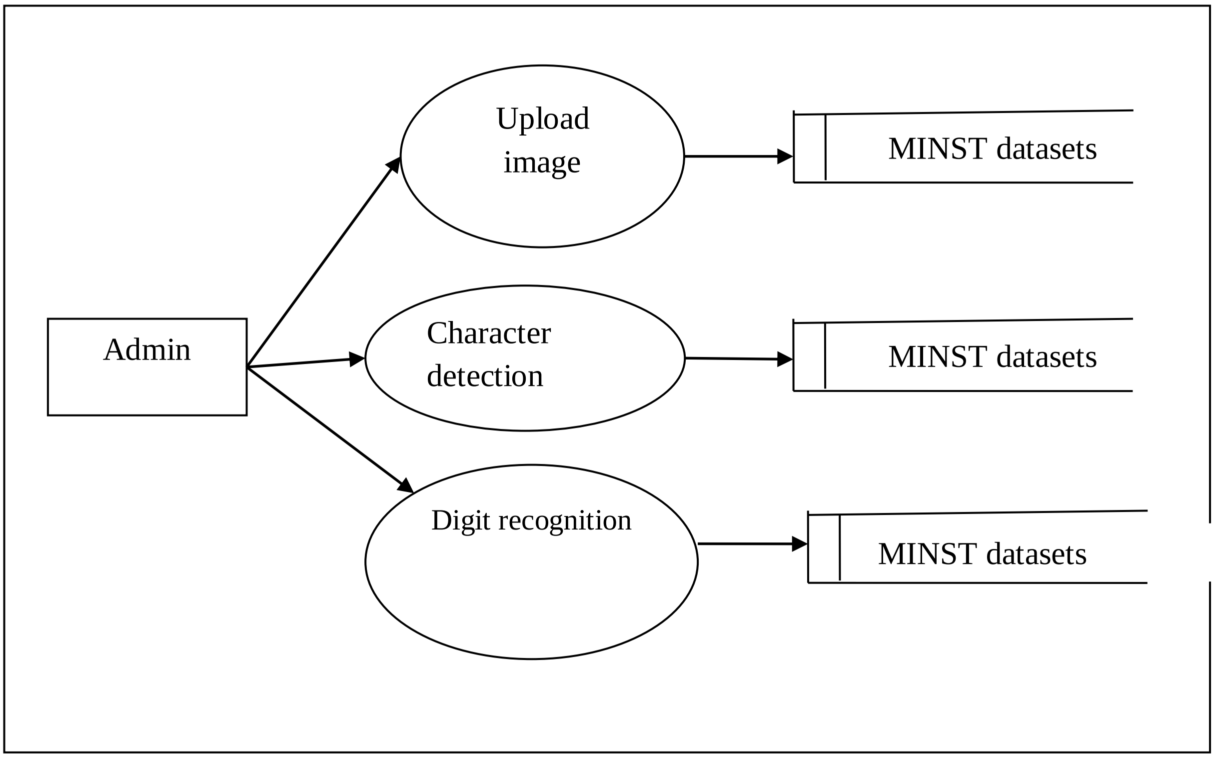
LEVEL 0

The Level 0 DFD shows how the system is divided into 'sub-systems' (processes), each of which deals with one or more of the data flows to or from an external agent, and which together provide all of the functionality of the system as a whole. It also identifies internal data stores that must be present in order for the system to do its job, and shows the flow of data between the various parts of the system.



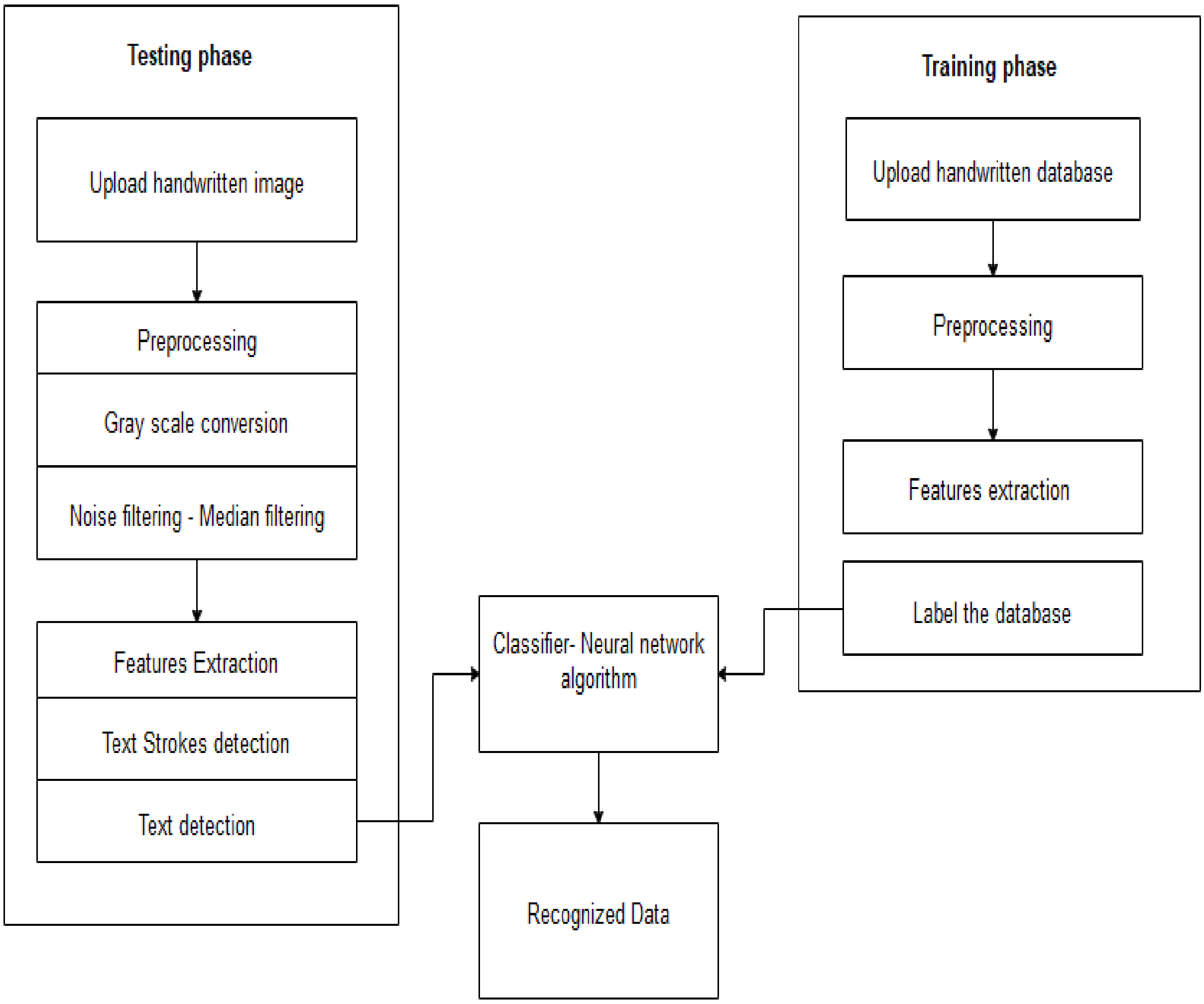
LEVEL-1

The next stage is to create the Level 1 Data Flow Diagram. This highlights the main functions carried out by the system. As a rule, to describe the system was using between two and seven functions - two being a simple system and seven being a complicated system. This enables us to keep the model manageable on screen or paper.

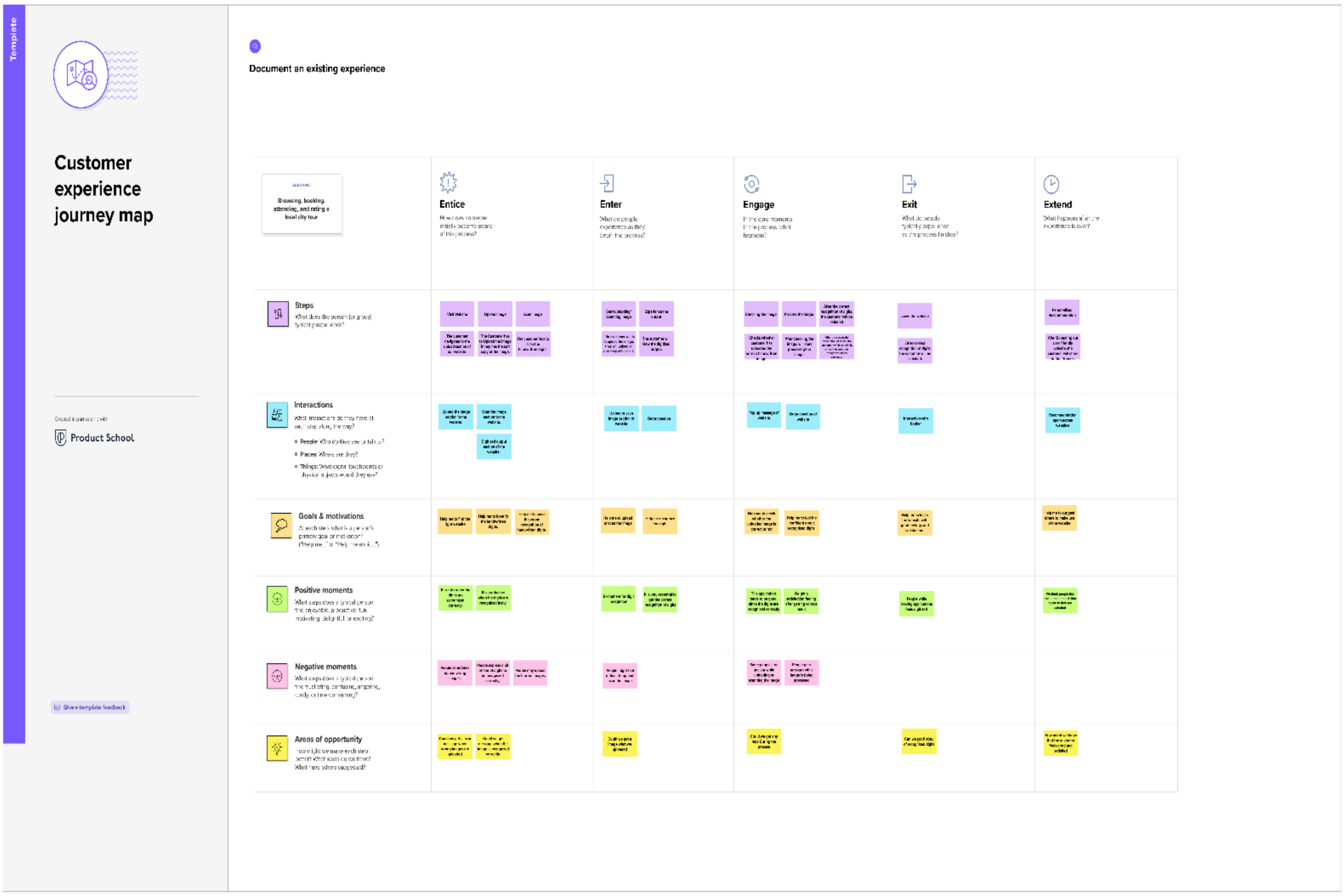


5.2 SOLUTION & TECHNICAL ARCHITECTURE

In this architecture, we can spilt the framework into two phases such as training and testing phase. Training phase, train the hand digit images and in test phase, input the hand digit image. Then implement CNN algorithm to classify the digits with improved accuracy. Fig 6.1 shows the overall architecture.



5.3 USER STORIES



6. PROJECT PLANNING & SCHEDULING

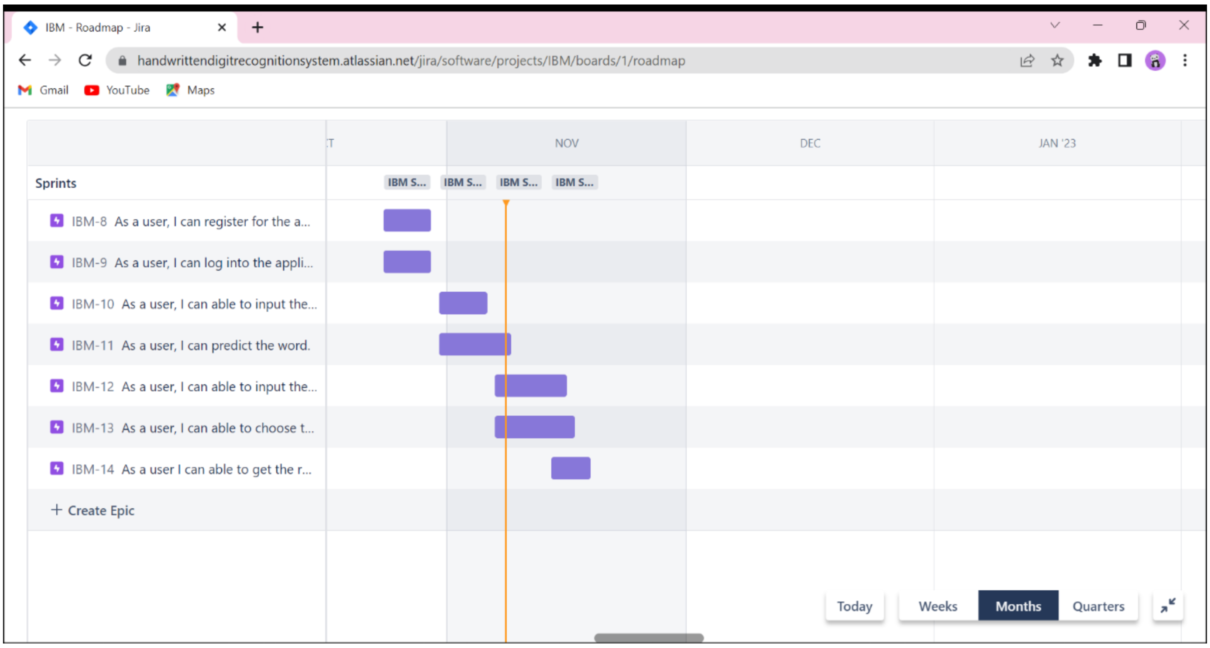
6.1 SPRINT PLANNING & ESTIMATION

TITTLE	DESCRIPTION	DATE
Prepare Empathy Map	Prepare Empathy Map Canvas to capture the user Pains & Gains, Prepare list of problem statements	24 SEPTEMBER 2022
Literature Survey & Information Gathering	Literature survey on the selected project & gathering information by referring the, technical papers,research publications etc.	28 SEPTEMBER 2022
Ideation	List the by organizing the brainstorming session and prioritize the top 3 ideas based on the feasibility & importance.	25 SEPTEMBER 2022
Proposed Solution	Creation of proposed solution document, which includes the novelty, feasibility of idea, business model, social impact, scalability of solution, etc.	23 SEPTEMBER 2022
Problem Solution Fit	Creation of problem solution fit document.	30 SEPTEMBER 2022
Solution Architecture	Creation of solution architecture document.	28 SEPTEMBER 2022
Customer Journey	Prepare the customer journey maps to understand the user interactions & experiences with the application.	20 OCTOBER 2022
Data Flow Diagrams	Draw the data flow diagrams and submit for review.	9 OCTOBER 2022
Technology Architecture	Prepare the technology architecture diagram.	10 OCTOBER 2022

6.2 SPRINT DELIVERY SCHEDULE

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority
Sprint-1	Home	USN-1	As a user, I can go to the home page of the handwritten digit recognition for detection.	2	Medium
Sprint-2	Upload image of handwritten digit or documents	USN-2	As a user, I can able to input the images of handwritten digit or documents to the application.	3	Low
Sprint-3	Prediction	USN-3	As a user, I can predict the word.	4	High
Sprint-4	Recognize digit	USN-4	As a user I can able to get the recognized digit as output from the images of digital documents or images.	2	Medium

6.3 REPORT FROM JIRA



7. CODING & SOLUTIONING

7.1 FEATURE 1

CLEAR IMAGE

This feature can be used to clear the image if we uploaded a wrong image or if we need to change the image. The clear button clears both the image value and the preview of the image in script tag.

```
<script>

$(document).ready(function() {
            $('#clear_button').on('click', function() {
                $('#image').val('');
                $('#frame').attr('src',"");
              });
          });

</scrip>
```

7.2 FEATURE 2

UPLOAD IMAGE WITH PREVIEW

A preview refers to a feature that lets you glimpse or view something in part or whole without it being opened. A picture preview would show a small version of the picture and give you a good idea what each picture is without opening each picture it is a useful feature created using JavaScript

```
<section id="content">

      <div class="leftside">
      <form action="/predict" method="POST" enctype="multipart/form-data">
      <label>Select a image:</label>
      <input id="image" type="file" name="image" accept="image/png, image/jpeg"
onchange="preview()"><br><br>
        <img id="frame" src="" width="100px" height="100px"/>
        <div class="buttons_div">
          <button type="submit" class="btn btn-dark" id="predict_button">Predict</button>
          <button type="button" class="btn btn-dark" id="clear_button">  Clear
 </button>
        </div>
      </form>
      </div>
</section>
```

8. TESTING

8.1 TEST CASES

A test case has components that describe input, action and an expected response, in order to determine if a feature of an application is working correctly. A test case is a set of instructions on “HOW” to validate a particular test objective/target, which when followed will tell us if the expected behavior of the system is satisfied or not.

Characteristics of a good test case:

- Accurate: Exacts the purpose.
- Economical: No unnecessary steps or words.
- Traceable: Capable of being traced to requirements.
- Repeatable: Can be used to perform the test over and over.
- Reusable: Can be reused if necessary

S.NO	FUNCTION	DESCRIPTION	EXPECTED OUTPUT	ACTUAL OUTPUT	STATUS
1	Framework construction	Generate the GUI for admin and user	Individual page for admin and user	Individual page for admin and user	Success
2	Read the comments	Comments analysis	Comments in text format	Comments in text format	Success
3	Classification	Classify the datasets	Negative comments	Negative comments	Success
4	Rules implementation	Block the comments and friends	Block the users	Block the users	Success

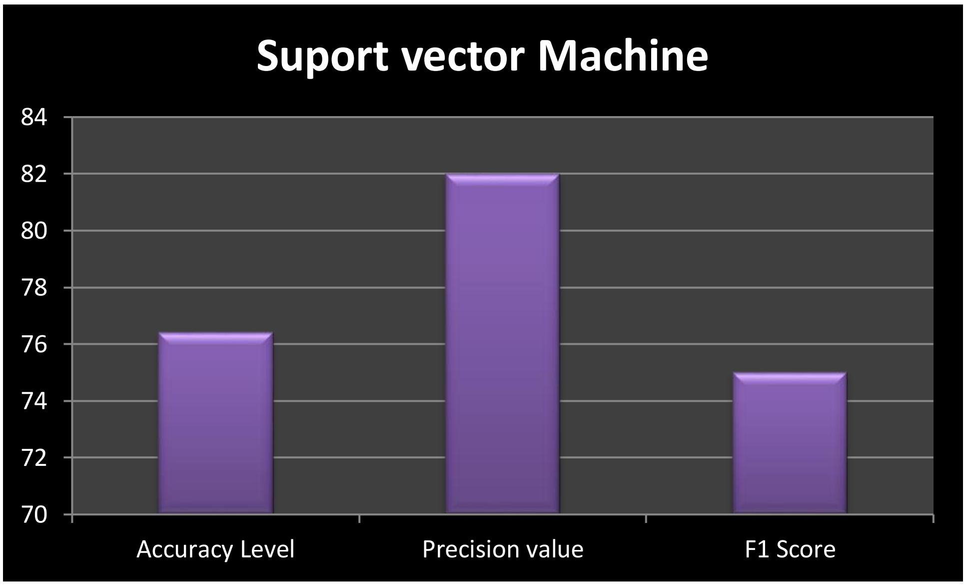
8.2 USER ACCEPTANCE TESTING

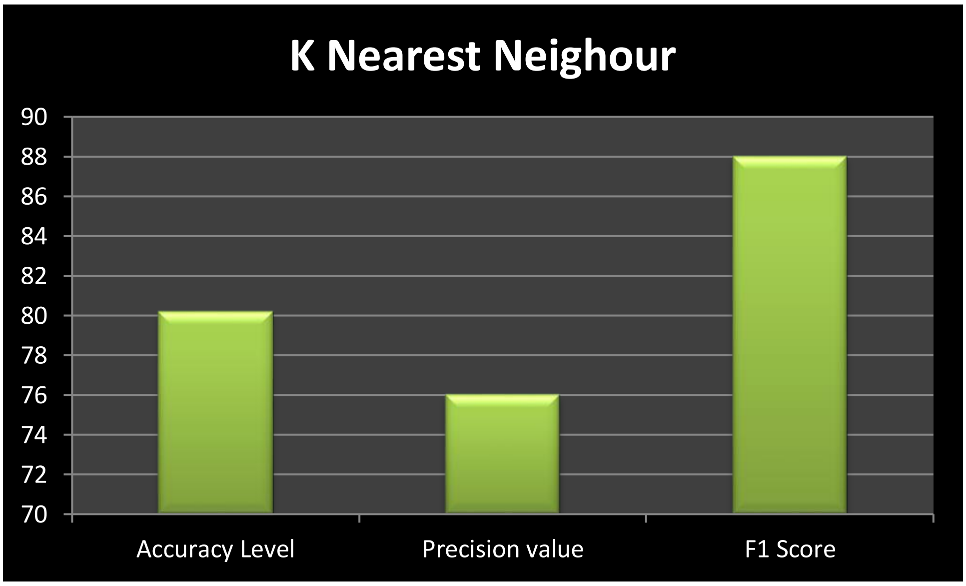
Acceptance testing can be defined in many ways, but a simple definition is the succeeds when the software functions in a manner that can be reasonable expected by the customer. After the acceptance test has been conducted, one of the two possible conditions exists. This is to fine whether the inputs are accepted by the database or other validations. For example accept only numbers in the numeric field, date format data in the date field. Also the null check for the not null fields. If any error occurs then show the error messages. The function of performance characteristics to specification and is accepted. A deviation from specification is uncovered and a deficiency list is created. User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

9. RESULTS

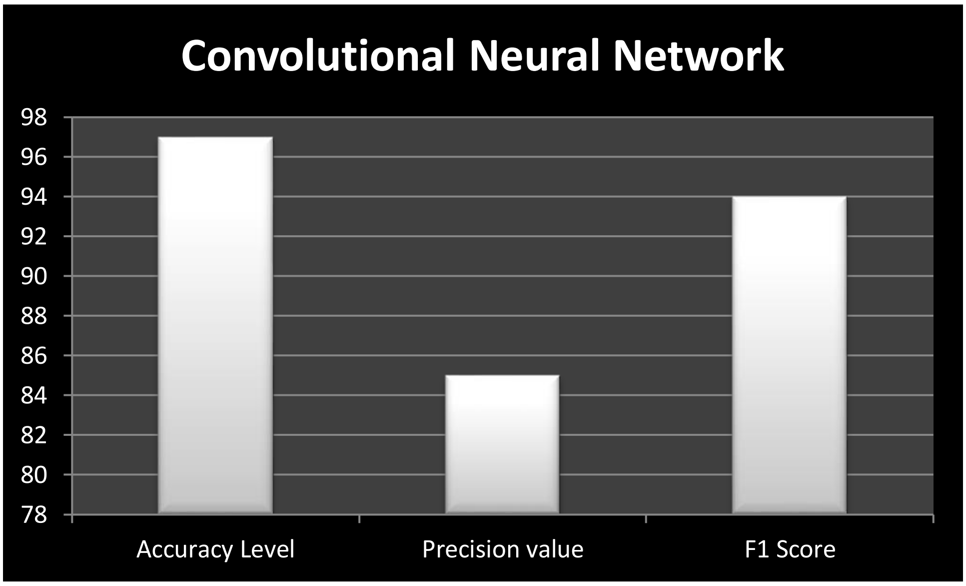
9.1 PERFORMANCE METRICS

Existing Algorithm





Proposed Algorithm



10. ADVANTAGES & DISADVANTAGES

ADVANTAGES

- Reduce the time and computational complexity
- Relevant text strokes are detected
- Provide improved classification accuracy
- Implemented in real time environments

DISADVANTAGES

- Time complexity can be high
- Redundant features are extracted
- So classification accuracy is less
- Only detect the text in printed documents

11. CONCLUSION

A recognition system for handwritten digit has attracted some interests in the research community by introduction of large dataset. In this work, convolutional neural networks were applied for handwritten digit recognition. The goal was the recognition of patterns taken from the MNIST database. CNNs were modified by the use of contour features, which are known as good feature extractors. The results demonstrated that CNNs perform pattern recognition effectively, incorporating in its structure some feature extraction and feature mapping characteristics, which are extremely adapted to invariances usually found in pattern recognition problems. Likewise, it was shown that Contour features can be appropriately incorporated in a CNN architecture, because such methods own similar principles. The effectiveness of the soft max method in classification improvement is also confirmed

12. FUTURE SCOPE

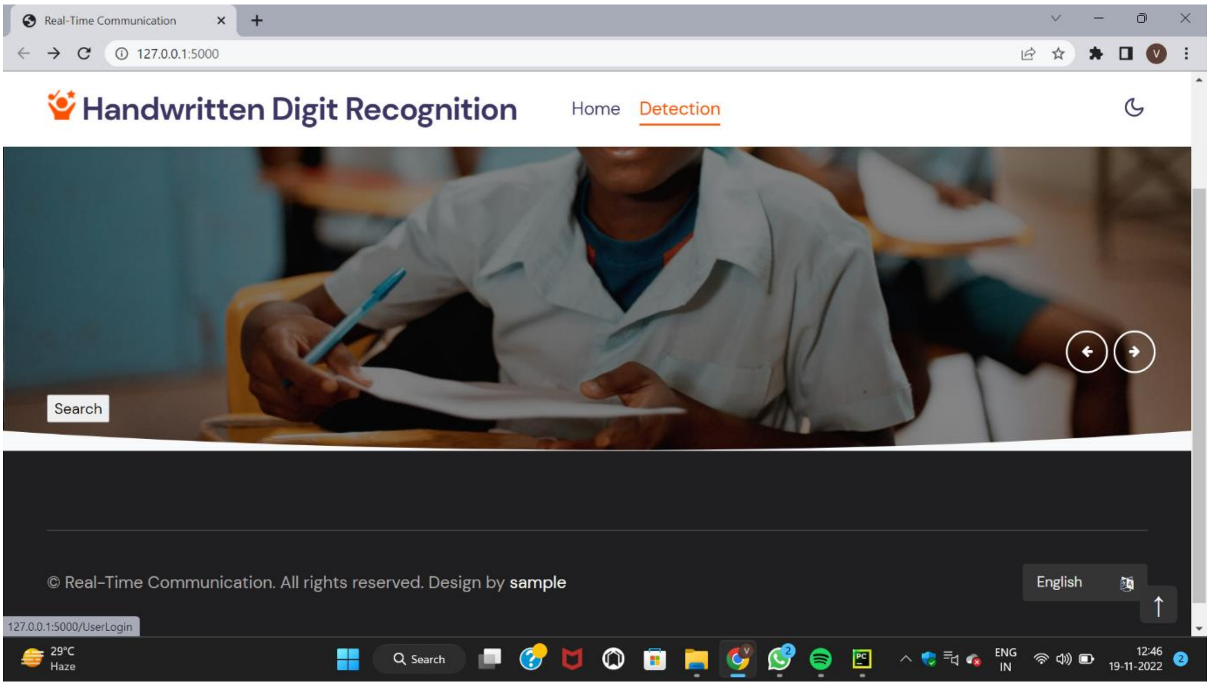
The future development of the applications based on algorithms of deep and machine learning is practically boundless. In the future, work on a denser or hybrid algorithm than the current set of algorithms with more manifold data to achieve the solutions to many problems can be done.

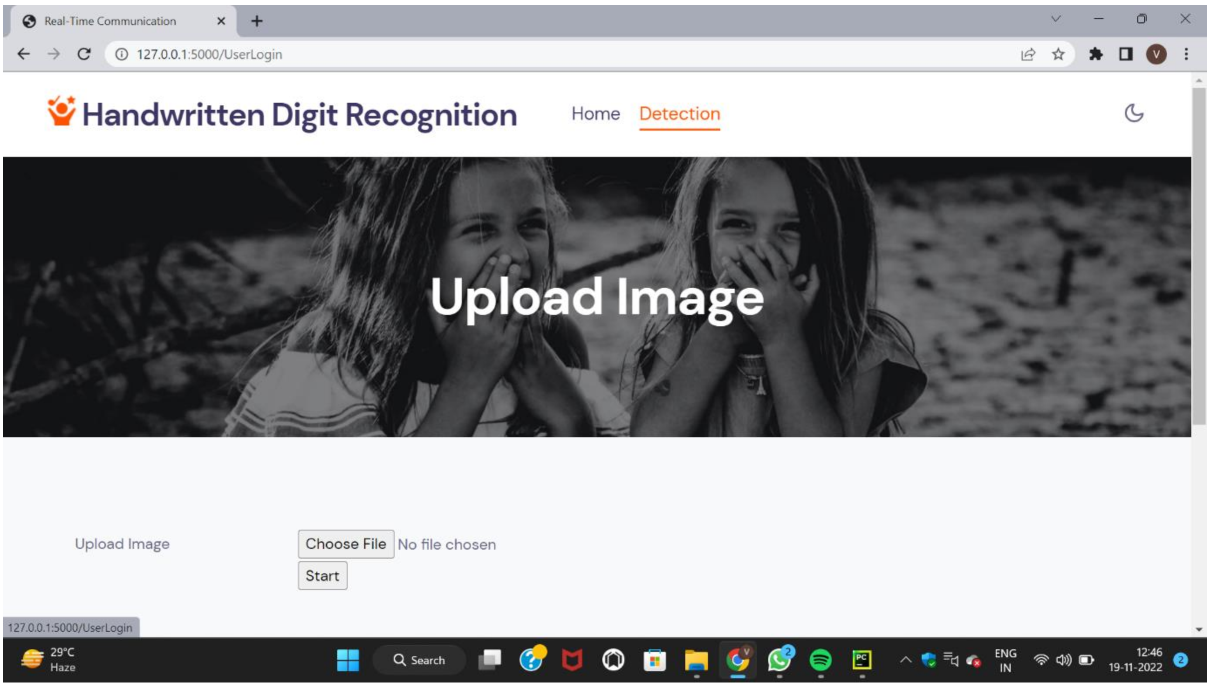
13. APPENDIX

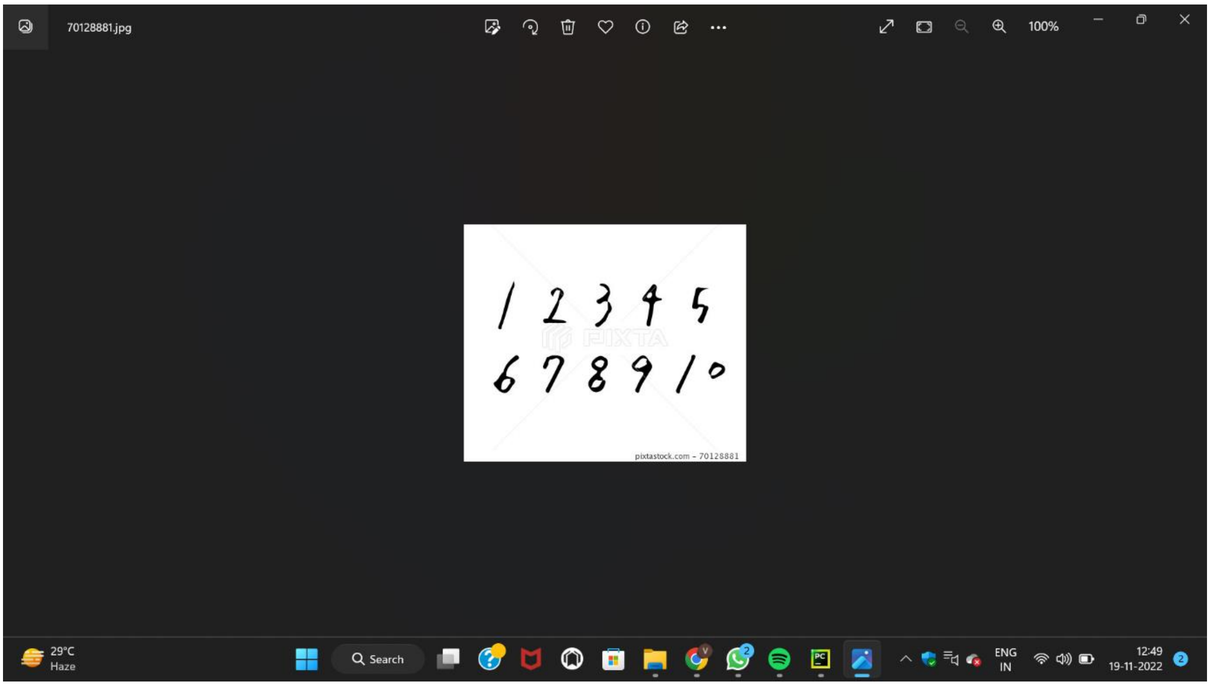
13.1 SOURCE CODE

```
from keras import layers
from keras import models
from keras.datasets import mnist
from keras.utils import to_categorical

(train_images, train_labels), (test_images, test_labels) =
mnist.load_data()

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28,
1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
model.summary()

train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255
test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)

model.compile(optimizer='rmsprop', loss='categorical_crossentropy',
metrics=['accuracy'])
model.fit(train_images, train_labels, epochs=5, batch_size=64)

test_loss, test_acc = model.evaluate(test_images, test_labels)

print(test_acc)

model.save('mnist.h5')
```

SCREEN SHOTS



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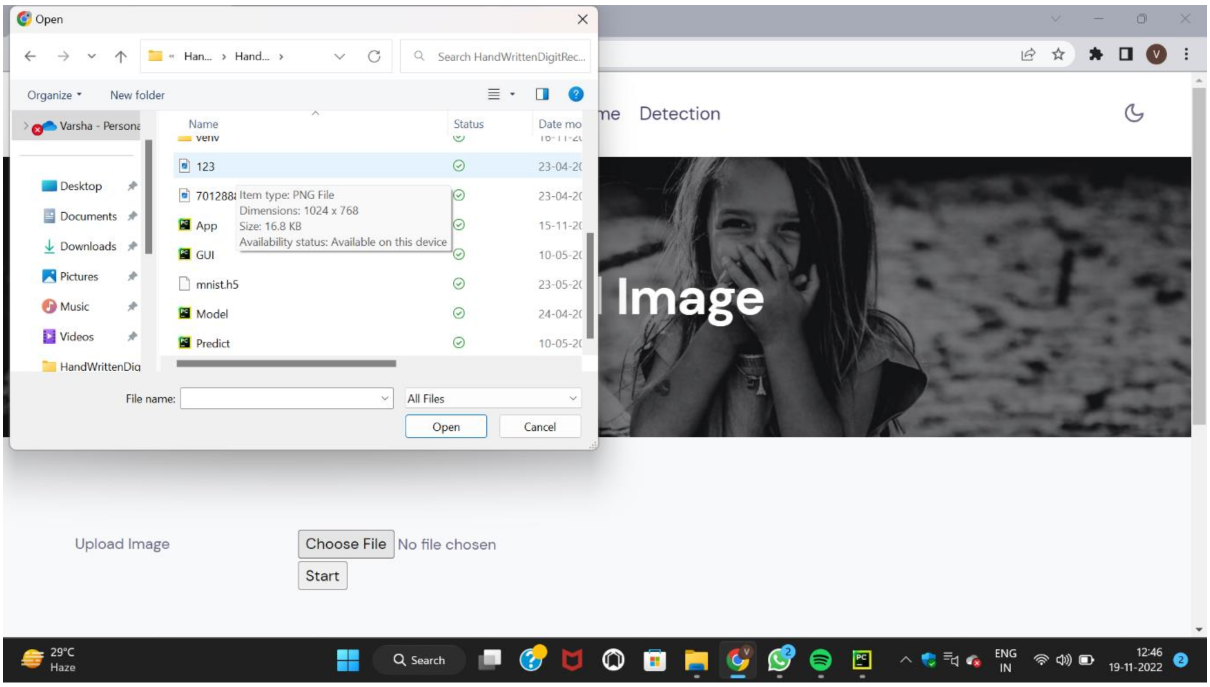
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Organize
New folder
Varsha - Personal
Desktop
Documents
Downloads
Pictures
Music
Videos
HandWrittenDig
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App
GUI
mnist.h5
Model
Predict
Item type: PNG File
Dimensions: 1024 x 768
Size: 16.8 KB
Availability status: Available on this device
File name:
All Files
Open
Cancel
Detection
Image
Upload Image
Choose File
No file chosen
Start
29°C
Haze
Search
ENG
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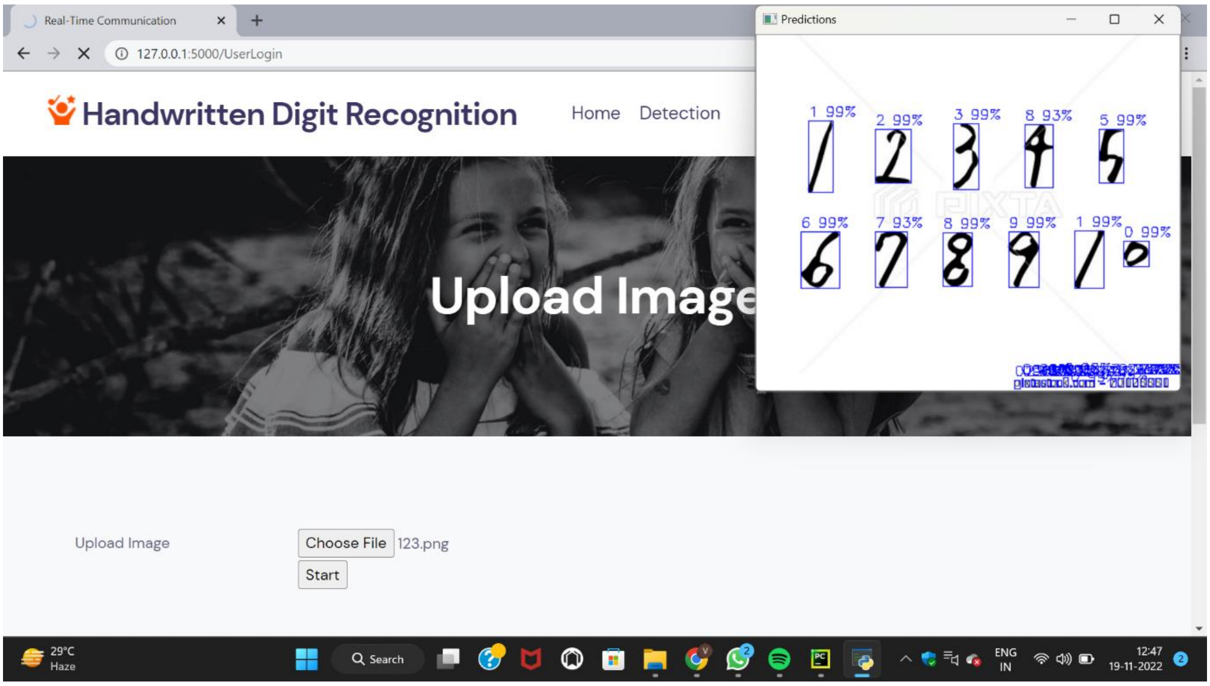
19-11-2022



GITHUB & PROJECT DEMO LINK

Demo Video link in drive:

https://drive.google.com/file/d/1GCdWFPaxNgyo975Nd6l2Iv1SXRkpvNkO/view?usp=sharing

Final Deliverables link in github:

https://github.com/IBM-EPBL/IBM-Project-20914-1659766582/tree/main/Final%20Deliverables