



LOYOLA INSTITUTE OF TECHNOLOGY,CHENNAI

ANNA UNIVERSITY::CHENNAI – 600025

**PROJECT TITLE: HANDWRITTEN RECOGNITION USING MACHINE
LEARNING**

A NALAIYA THIRAN PROJECT REPORT

SUBMITTED BY

TEAM SIZE : 4

TEAM LEADER :SASIDHARAN S (210919205048)

TEAM MEMBER :DHINADHAYALAN R (210919205013)

TEAM MEMBER : JAYARAJ J B (210919205025)

TEAM MEMBER : MANIKANDAN V (210919205029)

TEAM ID : PNT2022TMID25747

MENTOR NAME: Mrs .VANITHA B

EVALUATOR NAME : Mrs.SAROJINI PREMALATHA J

TABLE OF CONTENT

CHAPTER	TITLE	PAGE NO
	ABSTRACT	4
	LIST OF KEYWORDS	4
1.	INTRODUCTION	5
1.1	OBJECTIVE	6
1.2	LITERATURE SURVEY	7
2	PROJECT STATEMENT	12
2.1	PROBLEM STATEMENT	12
2.2	DISADVANTAGE	12
2.3	PROPOSED SYSTEM	13
2.4	ADVANTAGES	13
3	ARCHITECTURE	14
3.1	STATEMENT ARCHITECTURE	14

3.2	TRAINING VS TESTING GRAPH	14
4.	SYSTEM REQUIREMENT	15
4.1	HARDWARE REQUIREMENT	15
4.2	SOFTWARE REQUIREMENT	15
5.	SOURCE CODE	16
5.1	App.py	16
5.2	Index.html	17
5.3	Predict.html	19
5.4	Jupyter Notebook(IBM Cloud Deployment)	20
5.5	OUTPUT	24
5.6	IBM CLOUD DEPLOYMENT WITH TRAINING AND TESTING DATASETS	24
5.7	FLASK WEB APPLICATION	25
6	CONCLUSION	27
	REFERENCE	28

ABSTRACT

Images are easily processed and analysed by the human brain. When the eye sees a particular image, the brain is able to instantly segment it and recognize its numerous aspects. This project proposes the Deep Learning conceptual models based on Convolution Neural Network (CNN). Handwriting character recognition has become a popular subject of research. Different techniques and methods are used to develop a Handwriting Digits recognition system. The image dataset with 530 number of training images and 2756 numbers of testing images are used to experiment the proposed network. Handwriting characters/Digits remain complex since different individuals have different handwriting styles. Handwriting Digits recognition refers to the computer's ability to detect and interpret intelligible Handwriting input from Handwriting sources such as touch screens, photographs, paper documents, and other sources. Handwriting remains relevant, but people still want to have Handwriting copies converted into electronic copies that can be communicated and stored electronically. This project main objective is to report the development of a Handwriting Digit recognition system that will be used to read Handwriting Digit which is recognized based on the train and testing of MNIST datasets.

LIST OF KEYWORDS :

Convolution Neural Network (CNN), Handwritten Character Recognition, Optical Character Recognition, Support Vector Machine (SVM), Deep Learning, Machine Learning, Multi-Layered Perceptron (MLP), MNIST datasets.

CHAPTER 1

1.INTRODUCTION

Handwriting recognition is one of the compelling research works going on because every individual in this world has their own style of writing. 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. This image is analyzed by the model and the detected result is returned on to UI.

This paper aims to extensively simplify a user's experience in converting physical documents into digital files, and store them in such a way that they can be swiftly retrieved at all times. To achieve this, the paper proposes a model to convert a handwritten image into a text document. This document can be edited, stored or copied for further usage. OpenCV and Keras packages are used for training and model creation. A combination of neural networks such as CNN and RNN is used for character recognition. The neural network must understand the writing style of individual writers to be inclusive of words, alphabets and symbols written in all types of handwritings.

In today's day and age everything is digitised, which saves time and manpower to manually store or find from huge logs of physical files. Handwriting recognition makes it easier for us to store written data without manually typing it into a text document. This saves users a tremendous amount of time and effort to store and restore the document. Handwriting recognition is an essential process of image recognition . This deals with recognising an image, and classifying the handwritten content from it to a typed document form. This process can help solve many issues related to conversion and preserving necessary data from images, like finding relevant text from a large set of files, bank check analysis, and handwritten processing on legal forms. This is quite a challenging problem since everyone has a unique style of handwriting, most of whom write non-linearly. Images may not be captured properly due to poor camera quality, inadequate lighting, shaky hands, etc, which makes it challenging for machines to recognize and extract data accurately. Instead of manually checking and searching for a text in a physical document, our application makes it easier for users to search the words within a scanned document.

1.1 OBJECTIVE

This is Deep learning project, or we say Machine learning project in which we will create a Convolutional neural network(CNN) model with the help of tensorflow and keras which will recognise Handwritten characters, i.e English alphabets from A-Z. The dataset on which we will train our model contains a large number of images of English alphabets.

For image recognition and processing, there is a very popular artificial neural network used that is Convolutional neural network (CNN) that is specifically designed to process pixel data. And that's why we are going to build a CNN model to recognise character.

1.2. LITERATURE SURVEY

I.Bangla Handwritten Digit Recognition and Generation.

Published in: <https://arxiv.org/abs/2103.07905>.

Related DOI : https://doi.org/10.1007/978-981-13-7564-4_46

Date :14 Mar 2021

Abstract:

This article discusses the theme of creating the service that specializes in accounting for reading activities. The purpose of the research is to create methods of classifying and sorting literary works that can be integrated into any literary digital resource to expand its functionality. The created service is an Android application, which provides functions for keeping a reading diary and creating literary recommendations based on works added to the user's personal library. One of the complementary options of the application is the feature of expanding the literature base by scanning ISBN code of books that are not in the Google Books database. Handwritten digit or numeral recognition is one of the classical issues in the area of pattern recognition and has seen tremendous advancement because of the recent wide availability of computing resources. Plentiful works have already done on English, Arabic, Chinese, Japanese handwritten script. Some work on Bangla also have been done but there is space for development. From that angle, in this paper, an architecture has been implemented which achieved the validation accuracy of 99.44% on BHAND dataset and outperforms Alexnet and Inception V3 architecture. Beside digit recognition, digit generation is another field which has recently caught the attention of the researchers though not many works have been done in this field especially on Bangla. In this paper, a Semi-Supervised Generative Adversarial Network or SGAN has been applied to generate Bangla handwritten numerals and it successfully generated Bangla digits.

II. Handwritten Digit Recognition using Machine Learning Algorithms.

Published in: Global Journals

Online ISSN: 0975-4172 & **Print ISSN:** 0975-4350

Author: S M Shamim, Mohammad Badrul Alam Miah

Date : Year 2018

Abstract:

Handwritten character recognition is one of the practically important issues in pattern recognition applications. The applications of digit recognition includes in postal mail sorting, bank check processing, form data entry, etc. The heart of the problem lies within the ability to develop an efficient algorithm that can recognize hand written digits and which is submitted by users by the way of a scanner, tablet, and other digital devices. This paper presents an approach to off-line handwritten digit recognition based on different machine learning technique. The main objective of this paper is to ensure effective and reliable approaches for recognition of handwritten digits. Several machines learning algorithm namely, Multilayer Perceptron, Support Vector Machine, Naïve Bayes, Bayes Net, Random Forest, J48 and Random Tree has been used for the recognition of digits using WEKA. The result of this paper shows that highest 90.37% accuracy has been obtained for Multilayer Perceptron. Identification of digit from where best discriminating features can be extracted is one of the major tasks in the area of digit recognition system. To locate such regions different kind of region sampling techniques are used in pattern recognition [4]. The challenge in handwritten character recognition is mainly caused by the large variation of individual writing styles [5]. Hence, robust feature extraction is very important to improve the performance of a handwritten character recognition system. Nowadays handwritten digit recognition has obtained lot of concentration in the area of pattern recognition system sowing to its application in diverse fields. In next days, character recognition system might serve as a cornerstone to initiate paperless surroundings by digitizing and processing existing paper documents. Handwritten digit dataset are vague in nature because there may not always be sharp and perfectly straight lines.

III.Comparative Analysis of Algorithms Used in Handwritten Digit Recognition.

Published in: June 2021

Online ISSN: 2395-0056

Author: Dr. Anjana S Chandran, Athila V

Abstract:

Handwriting style differ from person to person. The handwritten digits are not always in the same width, size and orientation. In order to develop a system to understand this, includes a machine to recognize and classify the images of handwritten digits as ten digits (0 to 9). It is widely used by researchers for many applications such as computerized bank check numbers reading. Various machine learning and deep learning algorithms are used for this purpose. This paper focus on recognizing the handwritten digits i.e. 0 to 9 from the well-known MNIST dataset were 60000 samples are used for training the model and 10000 samples are used for testing the model. A comparative analysis of machine learning algorithms such as Decision tree, Logistic regression, k-nearest neighbors (KNN) and deep learning algorithm Convolutional Neural Network (CNN) is presented in this paper. In order to test the efficiency of these algorithm, the dataset is preprocessed and given as input to the algorithm and its precision, recall, f1 score and accuracy are found and compared. A digit recognition system is the functioning of a machine to recognize the digits from different sources like bank cheque, emails, papers, images, etc. The handwritten digit recognition is the capability of computers or machine to recognize digits that are handwritten by humans. In order to develop a system to understand handwritten digit, includes a machine to recognize and classify the images of handwritten digits as ten digits (0 to 9). The handwritten digits aren't always of equivalent size, width, orientation and justified to margins and the uniqueness and variety in the handwriting of different person also influence the formation and appearance of the digits The idea of reading handwritten digit, characters and words by computer systems are often said to be an imitation of a human being. Artificial intelligence is used to read handwriting from any handwriting source or images.

IV. A Multi-language Handwritten Digit Recognition Dataset.

Published in: 8 Apr 2020

Author: Weiwei JIANG

Abstract:

In this letter, we contribute a multi-language handwritten digit recognition dataset named MNIST-MIX, which is the largest dataset of the same type in terms of both languages and data samples. With the same data format with MNIST, MNIST-MIX can be seamlessly applied in existing studies for handwritten digit recognition. By introducing digits from 10 different languages, MNIST-MIX becomes a more challenging dataset and its imbalanced classification requires a better design of models. We also present the results of applying a LeNet model which is pre-trained on MNIST as the baseline. key words: Deep Learning, Handwritten Digit Recognition, Convolutional Neural Network. Handwritten digit recognition is a classical but important problem in computer vision, which has a wide application in different areas and can be embedded into larger systems. As a popular benchmark dataset, MNIST has been widely used for benchmarking different recognition models. Nowadays, with the development of deep learning represented by convolutional neural networks, MNIST becomes too easy for modern deep learning models. Even a CNN model with only three layers can achieve an accuracy better than 99% on MNIST, which indicates that MNIST is not enough for the performance evaluation of more sophisticated models.

V. Handwritten Character Recognition based on Artificial Neural Network,

Published in: Global Journals

Online E-ISSN: 2347-2693

Author: Rajdeep Singh

Date :11, Nov 2018

Abstract:

In current scenario, character recognition is the most important field of pattern recognition because of its application in numerous fields. Optical Character Recognition (OCR) and Handwritten Character Recognition (HCR) has specific domain to use. OCR system is most fitted for the applications like multi selection examinations, written communication address resolution etc. In returning days, character recognition system would possibly function a key issue to make paperless setting by digitizing and process existing paper documents. During this paper, we have planned the detail study on existing strategies for hand written character recognition based on ANN. This paper presents an in depth review within the field of handwritten Character Recognition. The OCR actually is a converter which translates hand written text images to a machine based text. In general, hand written recognition is classified in two ways: offline and online. Here, the writing is basically capture optically by scanner the completed writing text is scanned by a scanner in to digital format. That brings increase speed & precision to the entire recognition process. Handwritten recognition has been one of the most fascinating & challenging research areas in the field of image processing & pattern recognition in the recent year. OCR is a field of study than encompass many different solving methods. ANN (Sandhu & Leon, 2009), support vector machines & statistical classifies seem to be the preferred solutions to the problem due to their proven accuracy in classifying new data.

CHAPTER 2

2.1.PROBLEM STATEMENT

- i. We added the ReLU activation function which is required to introduce non-linearity to the model. This will help the network learn non-linear decision boundaries. The last layer is a softmax layer as it is a multiclass classification problem.
- ii. After implementing all the three algorithms that are SVM, MLP and CNN we have compared their accuracies and execution time with the help of experimental graphs for perspicuous understanding. We have taken into account the Training and Testing Accuracy of all the models

2.2 DISADVANTAGE

- a) The extensive use of information and communication technology has generated large volumes of data storage.
- b) The data repositories might contain massive amount of useful information. In order to extract useful knowledge from these data repositories for making better decision, necessitate the need for proper methods of extracting knowledge.
- c) Machine learning is an important technique which extracts necessary knowledge and information such as association, patterns, changes and anomalies from various data repositories.

2.3 PROPOSED SYSTEM

Handwritten character recognition is an expansive research area that already contains detailed ways of implementation which include major learning datasets, popular algorithms, features scaling and feature extraction methods.

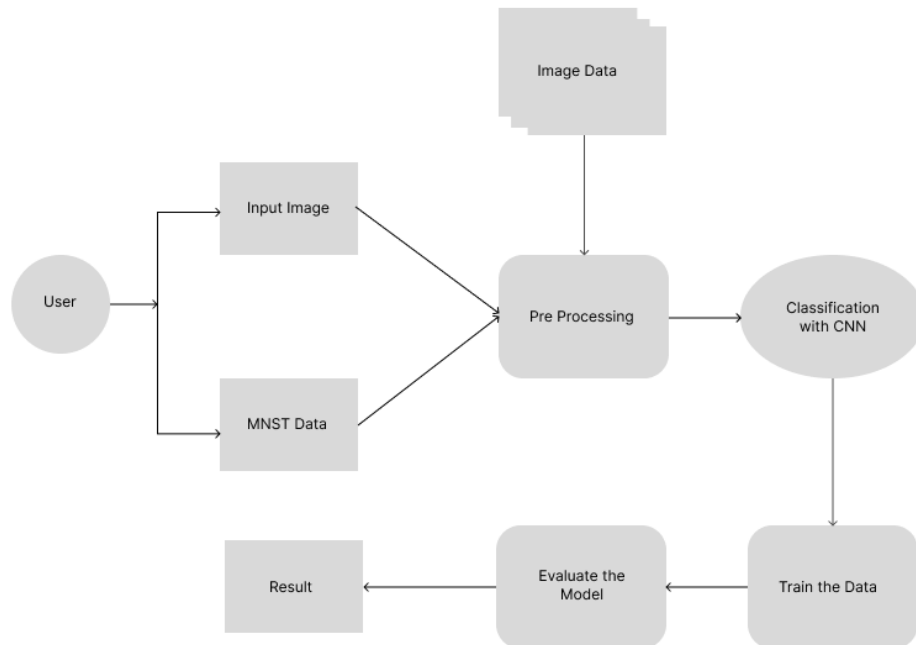
All we need is lots of data and information and we will be able to train a big neural net to do what we want, so a convolution can be understood as "looking at functions surrounding to make a precise prognosis of its outcome."

2.4 ADVANTAGE

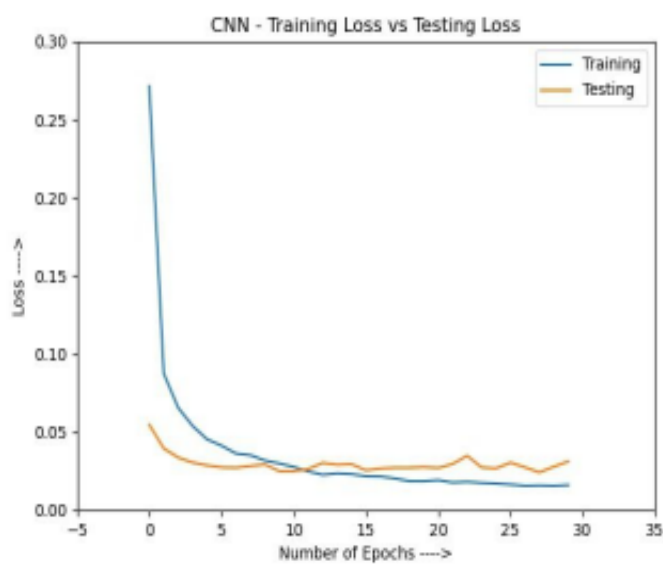
- Handwriting Recognition aims to design systems which are able to recognize handwriting of natural language
- Methods and recognition rates depend on the level of constraints on handwriting.
- Facilitates word recognition, spelling, vocabulary development, and other literacy skills needed to meet state standards.
- Supports the writing process and enables students to write independently and at an appropriate level.
- Supports student use of comprehension strategies at all stages of the reading process and promotes critical responses to text.
- Builds phonetic and spelling skills and increases recognition of patterns in words.
- Provides a scaffold for English Language Learners in the classroom.

CHAPTER 3

3.1 STATEMENT ARCHITECTURE



3.2 TRAINING VS TESTING GRAPH



CHAPTER 4

4. SYSTEM REQUIREMENT

4.1 HARDWARE REQUIREMENT

4.1 HARDWARE REQUIREMENT	
Hard Disk	500GB and Above
RAM	8GB and Above
Processor	I3 and Above

4.2 SOFTWARE REQUIREMENT

4.2 SOFTWARE REQUIREMENT	
Operating System	Windows 7 , 8, 10, 11 (64 bit)
Software	Visual Studio, Anaconda, Jupyter Notebook, Python.
Tools or Framework	Numpy, Tensorflow, Seaborn, Keras, Pandas, Matplotlib
Supported Devices	All Device and Web application.

CHAPTER 5

5 SOURCE CODE

5.1.App.py

```
import numpy as np
import os
from PIL import Image
from flask import Flask, request, render_template, url_for
from werkzeug.utils import secure_filename, redirect
from event.pywsgi import WSGIServer
from keras.models import load_model
from keras.preprocessing import image
from flask import send_from_directory

UPLOAD_FOLDER = 'C:\\Users\\hari9\\Desktop\\college\\Digit Recognition Flask App\\Datasets'

app = Flask(__name__)
app.config['UPLOAD_FOLDER'] = UPLOAD_FOLDER

model = load_model("mnistData.h5")

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['GET', 'POST'])
def upload():
    if request.method == "POST":
        f = request.files["image"]
        filepath = secure_filename(f.filename)
        f.save(os.path.join(app.config['UPLOAD_FOLDER'], filepath))

        upload_img = os.path.join(UPLOAD_FOLDER, filepath)
        img = Image.open(upload_img).convert("L")
        img = img.resize((28, 28))

        im2arr = np.array(img)
        im2arr = im2arr.reshape(1, 28, 28, 1)

        pred = model.predict(im2arr)

        num = np.argmax(pred, axis=1)
```



```

        return render_template('predict.html', num=str(num[0]))

if __name__ == '__main__':
    app.run(debug=True, threaded=False)

```

5.2.index.html:

```

<html>

<head>
  <title>Handwritten Digit Recognition Web Application</title>

  <metaname="viewport" content="width=device-width">
  <!--GoogleFont -->

  <linkhref="https://fonts.googleapis.com/css2?family=Prompt:wght@600&display=swap"rel
="stylesheet">

  <linkhref="https://fonts.googleapis.com/css2?family=Varela+Round&display=swap"rel="s
tylesheet">

  <linkhref="https://fonts.googleapis.com/css2?family=Source+Code+Pro:wght@500&display
=swap"rel="stylesheet">

  <linkhref="https://fonts.googleapis.com/css?family=Calistoga|Josefin+Sans:400,700|Pa
cifico&display=swap"rel="stylesheet">
  <!-- bootstrap -->

  <linkrel="stylesheet"href="https://stackpath.bootstrapcdn.com/bootstrap/4.3.1/css/bo
otstrap.min.css"integrity="sha384-
gg0yR0iXCbMQv3Xipma34MD+dH/1fQ784/j6cY/iJTQUOhcWr7x9JvoRxT2MZw1T"crossorigin="anonym
ous">
  <linkrel="stylesheet"type= "text/css"href= "{{
url_for('static',filename='css/style.css') }}">
  <!--fontawesome -->

  <scriptsrc="https://kit.fontawesome.com/b3aed9cb07.js"crossorigin="anonymous"></scri
pt>

  <scriptsrc="https://code.jquery.com/jquery-3.3.1.slim.min.js"integrity="sha384-
q8i/X+965Dz00rT7abK41JStQIAqVgRVzpbzo5smXKp4YfRvH+8abtTE1Pi6jizo"crossorigin="anonym
ous"></script>

  <scriptsrc="https://cdn.jsdelivr.net/npm/popper.js@1.14.7/umd/popper.min.js"integrity="sha384-

```

```

U02eT0CpHqdSJQ6hJty5KVphtPhzWj9W01clHTMGa3JDZwrnQq4sF86dIHNDz0W1"crossorigin="anonym
ous"></script>

<scriptsrc="https://stackpath.bootstrapcdn.com/bootstrap/4.3.1/js/bootstrap.min.js"i
ntegrity="sha384-
JjSmVgyd0p3pXB1rRibZUAYoIIy60rQ6VrjIEaFf/njGzIxFDs4x0xIM+B07jRM"crossorigin="anonym
ous"></script>
  <scriptsrc="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@latest"></script>

</head>

<script>
  functionpreview() {
    frame.src=URL.createObjectURL(event.target.files[0]);
  }

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

<body>

  <h1class="welcome">IBM PROJECT-A Novel Method For Handwritten Digit Recognition
  <divid="team_id">TEAM ID : PNT2022TMID25747</div>
</h1>
<sectionid="title">
  <h4class="heading">Handwritten Digit Recognition Website</h4>
  <br><br>
  <p>
    Here Select the Image to be Predicted and Press the button 'Read & Predict'
    to presdict the Digit that is to be recognized
  </p>

</section>

<sectionid="content">

  <divclass="leftside">
    <formaction="/predict"method="POST"enctype="multipart/form-data">
    <label>Select a image:</label>
    <inputid="image"type="file"name="image"accept="image/png,
image/jpeg"onchange="preview()"><br><br>
    <imgid="frame"src=""width="100px"height="100px"/>

```

```

        <div class="buttons_div">
            <button type="submit" class="btn btn-dark" id="predict_button">Read &
Predict</button>
            <button type="button" class="btn btn-dark" id="clear_button">&nbsp; Clear
&nbsp;</button>
        </div>
    </form>
</div>
</section>

</body>

</html>

```

5.3.Predict.html:

```

<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <title>Recognized Digit</title>
</head>
<style>
    body{
        background-image: url('static/images/Tech_Number.png');
        background-repeat: no-repeat;
        background-size: cover;
    }

    #rectangle{
        width:500px;
        height:200px;
        background-color: #202de4;
        border-radius: 25px;
        position: absolute;
        top:25%;
        left:50%;
        opacity: 0.8;
        transform: translate(-50%, -50%);
    }

    #ans{
        text-align: center;
        font-size: 40px;
        margin: 0 auto;
        padding: 3% 5%;
    }

```

```
padding-top: 15%;
color: white;
}

</style>
<body>
    <divid="rectangle">
        <h1id="ans">Recognized Digit is : {{num}}</h1>
    </div>
</body>
</html>
```

5.4.Jupyter Notebook(IBM Cloud Deployment):

```
import numpy as np
import tensorflow
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras import layers
from keras.layers import Dense, Flatten
from keras.layers import Conv2D
from keras.utils import np_utils
import matplotlib.pyplot as plt

#Load Data
(x_train, y_train), (x_test, y_test)=mnist.load_data ()

print (x_train.shape)
print (x_test.shape)

#Plot the Image
plt.imshow(x_train[7000])

np.argmax(y_train[7000])

#Reshaping the Datasets
x_train=x_train.reshape (60000, 28, 28, 1).astype('float32')
x_test=x_test.reshape (10000, 28, 28, 1).astype ('float32')

#Applying One Hot Encoding
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)

#Adding CNN Layer
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'))

#Compiling the Model
model.compile(loss= 'categorical_crossentropy', optimizer="Adam", metrics=['accuracy'])
x_train = np.asarray(x_train)
y_train = np.asarray(y_train)

#Train the Model
model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=5, batch_size=32)

#Observing the Metrics
metrics = model.evaluate(x_test, y_test, verbose=0)
print("Metrics [Test loss, Test Accuracy] : ")
print(metrics)

#Test The Model
prediction=model.predict(x_test[7000:7001])
print(prediction)

plt.imshow(x_test[7000])

import numpy as np
print(np.argmax(prediction, axis=1))

#Save the Model
model.save('models/mnistData.h5')

#View the Location
cd models

#IBM Cloud Deploy
from ibm_watson_machine_learning import APIClient
credentials = {
    "url": "https://eu-gb.ml.cloud.ibm.com",
    "apikey": "5rzQhIHUmvhPg67cgRRjqIHHie7GoUBaoUwwPmAietm"
}
client = APIClient(credentials)
client

client.spaces.get_details()

def guid_from_space_name(client,deploy):
    space = client.spaces.get_details()
    return (next(item for item in space['resources'] if
item['entity']['name']==deploy)['metadata']['id'])

space_uid = guid_from_space_name(client, 'Project')
print("Space UID = " + space_uid)

client.set.default_space(space_uid)

client.software_specifications.list(limit=100)

```

```

software_space_uid = client.software_specifications.get_uid_by_name('tensorflow_rt22.1-
py3.9')
software_space_uid

model_details = client.repository.store_model(model='handwritten-digit-recognition-
model_new.tgz',meta_props={
    client.repository.ModelMetaNames.NAME:"Digit recognition model",
    client.repository.ModelMetaNames.TYPE:"tensorflow_2.7",
    client.repository.ModelMetaNames.SOFTWARE_SPEC_UID:software_space_uid
})

model_details

model_id = client.repository.get_model_id(model_details)
model_id

client.repository.download(model_id,'DigitRecog_IBM_model.tar.gz')

ls

#Test the Model
from keras.models import load_model
from keras.preprocessing import image
from PIL import Image
import numpy as np

model = load_model("mnistData.h5")

import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

cos_client = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='vDJagj39pjgcYrtGJiuQhoS4FFW7NTixBi0vFbUtq_7d',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.eu-gb.cloud-object-storage.appdomain.cloud')

bucket = 'handwritten-digit-recognition88'
object_key = '4.png'

streaming_body_1 = cos_client.get_object(Bucket=bucket, Key=object_key)['Body']

#The IBM Object storage is where the Pictures has been uploaded to test the data via IBM Cloud

img = Image.open(streaming_body_1).convert("L") # convert image to monochrome
img = img.resize( (28,28) ) # resizing of input image

img

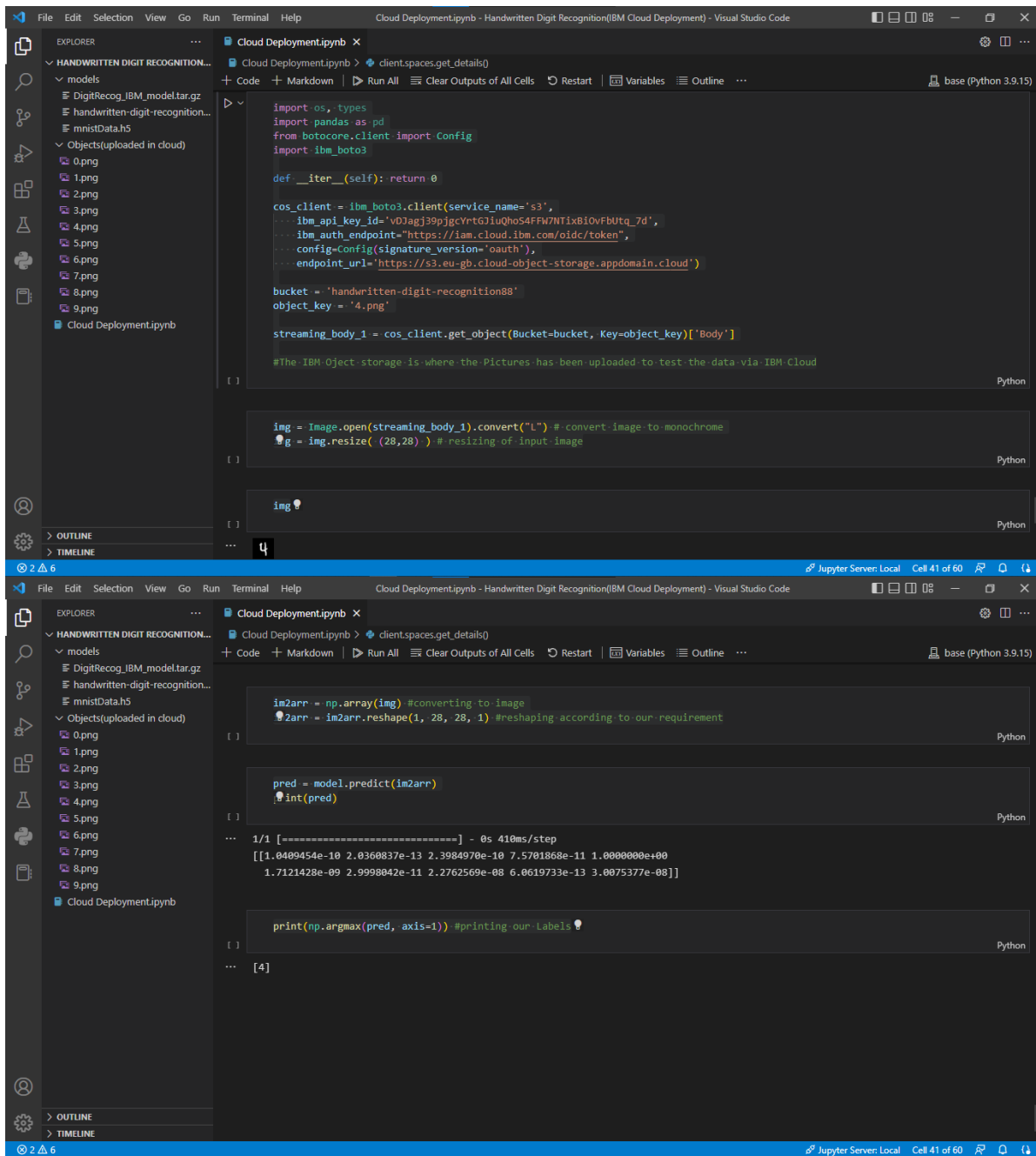
im2arr = np.array(img) #converting to image

```

```
im2arr = im2arr.reshape(1, 28, 28, 1) #reshaping according to our requirement  
  
pred = model.predict(im2arr)  
print(pred)  
  
print(np.argmax(pred, axis=1)) #printing our Labels
```

5.5. OUTPUT

5.6 IBM CLOUD DEPLOYMENT WITH TRAINING AND TESTING DATASETS



The image displays two screenshots of a Jupyter Notebook environment within Visual Studio Code, showing the deployment and testing of a digit recognition model on IBM Cloud.

Top Screenshot: The notebook is titled "Cloud Deployment.ipynb". The first cell shows the initialization of the IBM Cloud client and the retrieval of an object from the cloud storage. The code includes imports for `os`, `types`, `pandas`, `Config`, and `ibm_boto3`. The `__iter__` method is defined to return 0. The `cos_client` is initialized with the service name 's3', API key, auth endpoint, and endpoint URL. The `bucket` is 'handwritten-digit-recognition88' and the `object_key` is '4.png'. The `streaming_body_1` is retrieved from the cloud storage. A comment indicates that the IBM Object storage is where the pictures have been uploaded to test the data via IBM Cloud.

Bottom Screenshot: The notebook continues with the processing of the retrieved image. The second cell shows the image being opened and converted to grayscale, then resized to (28, 28). The third cell shows the image being converted to a NumPy array and reshaped to (1, 28, 28, 1). The fourth cell shows the prediction using the trained model, resulting in the digit 4. The final cell shows the prediction result, which is 4.

```
import os, types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

cos_client = ibm_boto3.client(service_name='s3',
                              ibm_api_key_id='v0Jagj39pjgcYrtG3iuQhoS4FFW7NTixBIOvFBUTq_7d',
                              ibm_auth_endpoint='https://iam.cloud.ibm.com/oidc/token',
                              config=Config(signature_version='oauth'),
                              endpoint_url='https://s3.eu-gb.cloud-object-storage.appdomain.cloud')

bucket = 'handwritten-digit-recognition88'
object_key = '4.png'

streaming_body_1 = cos_client.get_object(Bucket=bucket, Key=object_key)['Body']

#The IBM Object storage is where the Pictures has been uploaded to test the data via IBM Cloud

img = Image.open(streaming_body_1).convert("L") # convert image to monochrome
img = img.resize((28,28)) # resizing of input image

img

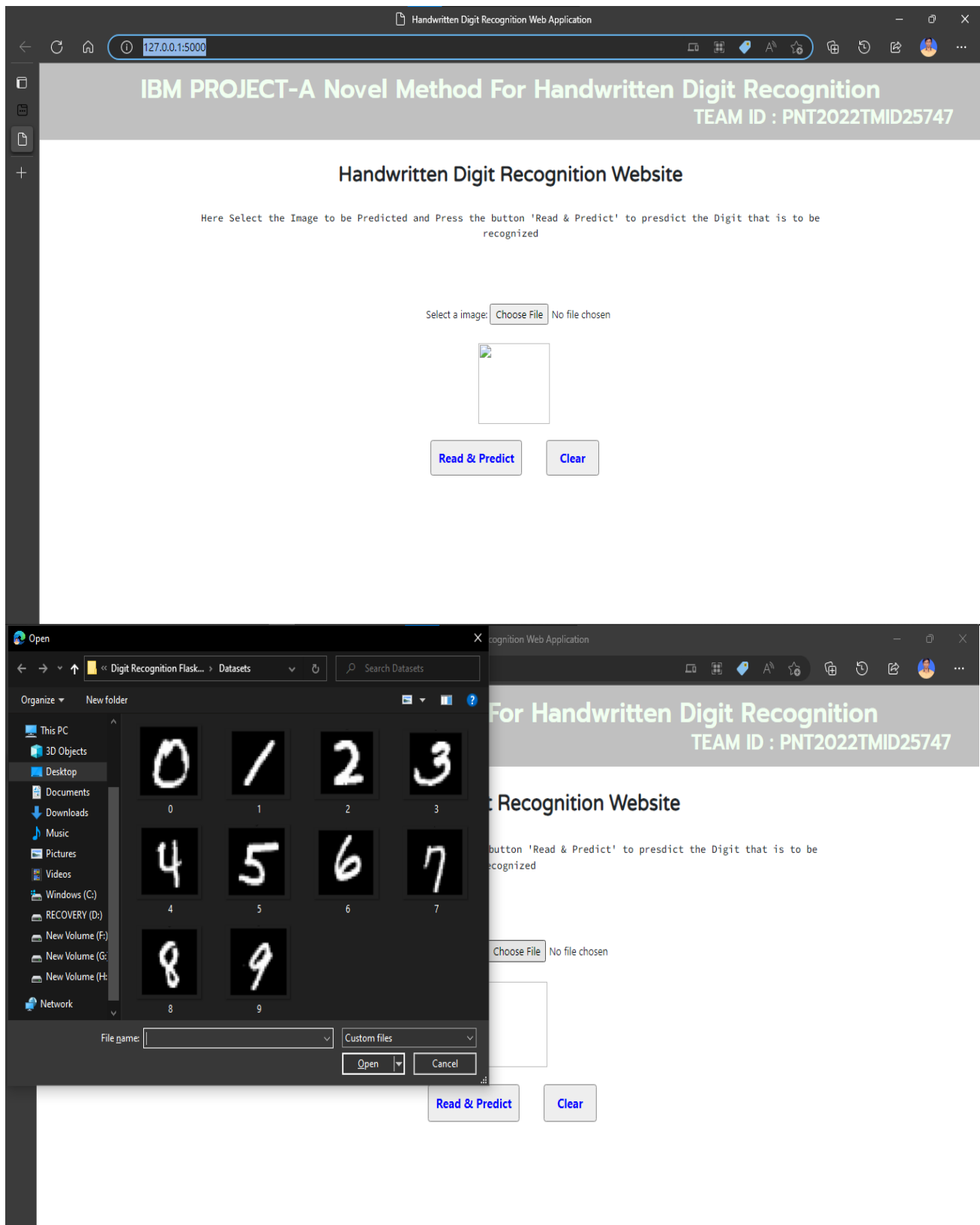
im2arr = np.array(img).#converting to image
im2arr = im2arr.reshape(1, 28, 28, 1) #reshaping according to our requirement

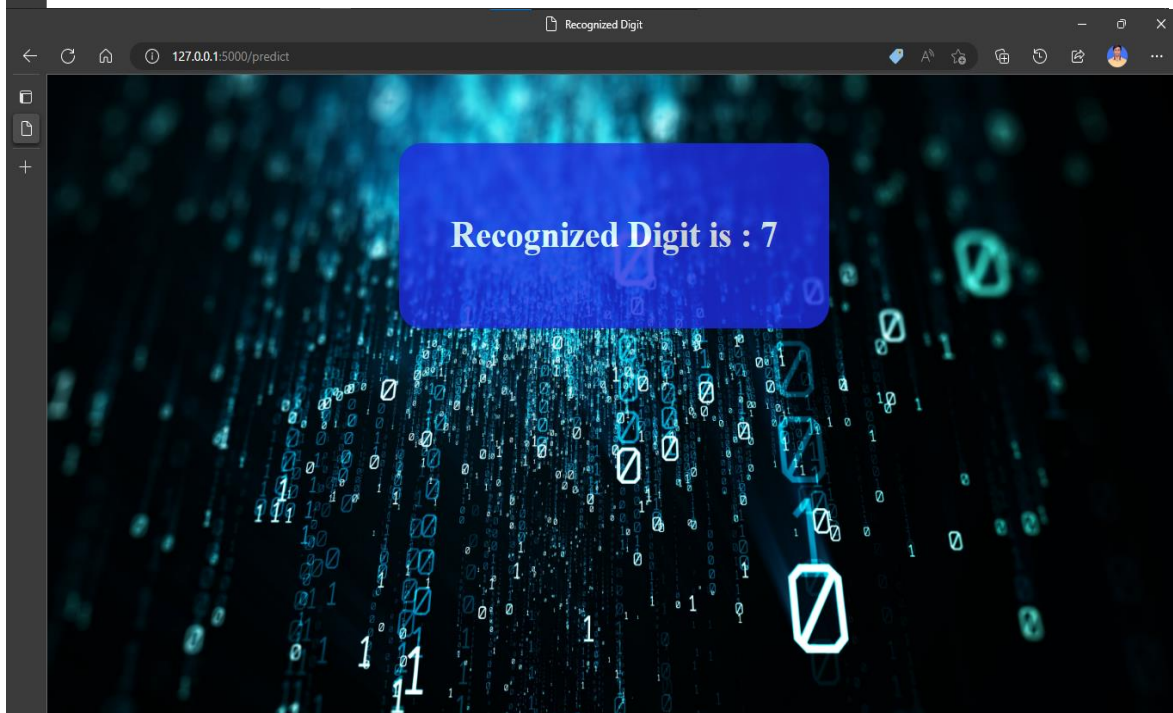
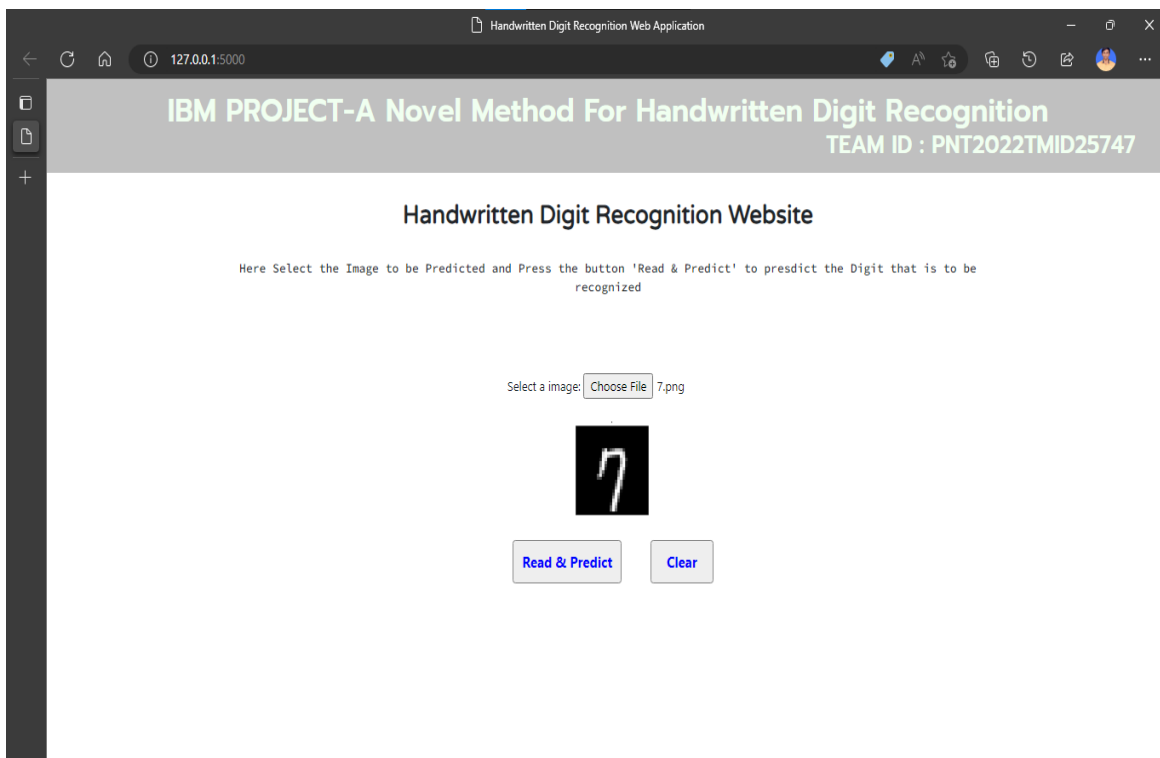
pred = model.predict(im2arr)
int(pred)

1/1 [=====] - 0s 410ms/step
[[1.0489454e-10  2.0360837e-13  2.3984970e-10  7.5701868e-11  1.0000000e+00
  1.7121428e-09  2.9998042e-11  2.2762569e-08  6.0619733e-13  3.0075377e-08]]

print(np.argmax(pred, axis=1)) #printing our Labels
[4]
```


5.7 FLASK WEB APPLICATION





CHAPTER 6

6. CONCLUSION

With the advancement in the AI field a wide range of Modeling of data and collection of data are required in order to create a Best Recognition system. So ,We created a AI model to recognition of the Handwritten Digit which help us to recognize the most complicated Digit with training the Datasets. Support vector machines are one of the basic classifiers that's why it's faster than most algorithms and in this case, gives the maximum training accuracy rate but due to its simplicity, it's not possible to classify complex and ambiguous images as accurately as achieved with MLP and CNN algorithms. We have found that CNN gave the most accurate results for handwritten digit recognition.

REFERENCES

- [1] Fischer, A., Frinken, V., Bunke, H.: Hidden Markovmodels for off-line cursive handwritingrecognition, in C.R. Rao (ed.): Handbook of Statistics 31, 421 – 442, Elsevier, 2013.
- [2] Frinken, V., Bunke, H.: Continuous handwrittenscript recognition, in Doermann, D., Tombre, K.(eds.): Handbook of Document Image Processing and Recognition, Springer Verlag, 2014.
- [3] S. Günter and H. Bunke. A new combinationscheme for HMM-based classifiers and itsapplication to handwriting recognition. In Proc.16th Int. Conf. on Pattern Recognition, volume 2,pages 332–337. IEEE, 2002.
- [4] U.-V. Marti and H. Bunke. Text line segmentationand word recognition in a system for generalwriter independent handwriting recognition. InProc. 6th Int. Conf. on Document Analysis andRecognition, pages 159– 163.
- [5] M. Liwicki and H. Bunke, “Iam-ondb - an on-lineEnglish sentence database acquired from thehandwritten text on a whiteboard,” in ICDAR, 2005.
- [6] A. Graves and J. Schmidhuber, “Offlinehandwriting recognition with multidimensionalrecurrent neural networks,” in Advances in neural information processing systems, 2009, pp. 545–552.
- [7] Nafiz Arica, and Fatos T. Yarman-Vural, —OpticalCharacter Recognition for Cursive Handwriting,IEEE Transactions on Pattern Analysis andMachine Intelligence, vol.24, no.6, pp. 801-113,June 2002.
- [8] Anita Pal and DavashankarSingh,”Handwritten English Character Recognition Using NeuralNetwork”, International Journal of Computer Science and Communication, pp: 141- 144, 2011.
- [9] Sandhya Arora, “Combining Multiple Feature Extraction Techniques for Handwritten Devnagari Character Recognition”, IEEE Region 10 Colloquium and the Third ICIIS, Kharagpur, INDIA, December 2008.
- [10]Om Prakash Sharma, M. K. Ghose, Krishna Bikram Shah, “An Improved Zone Based Hybrid Feature Extraction Model for Handwritten Alphabets Recognition UsingEuler Number”, International Journal of Soft Computing and Engineering (ISSN: 2231 - 2307), Vol. 2, Issue 2, pp. 504- 508, May 2012.

- [11]N. Venkata Rao and Dr.A.S.C.S.Sastry - Optical Character Recognition Technique Algorithms-2016 Journal of Theoretical and Applied Information Technology.
- [12]Ganapathy, V., & Liew, K. L. (2008). Handwritten Character Recognition Using Multiscale Neural Network Training Technique. World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering, 2(3), 638-643.
- [13]Grady, J. O. (2010). System Requirements Analysis. Amsterdam, Netherlands: Elsevier.
- [14]Gribaudo, M. (2013). Theory and Application of Multi-Formalism Modeling. Hershey, PA: IGI Global.
- [15]Gunawan, T. S., Noor, A. F. R. M., &Kartiwi, M. (2018). Development of english handwritten recognition using deep neural network. Indonesian Journal of Electrical Engineering and Computer Science, 10(2), 562-568.
- [16]Hertz, J. A. (2018). Introduction to the theory of neural computation. Boca Raton: CRC Press.
- [17]Hamid, N. A., &Sjarif, N. N. A. (2017). Handwritten recognition using SVM, KNN and neural network. arXiv preprint arXiv:1702.00723.
- [18]Kumar, P., Saini, R., Roy, P. P., & Pal, U. (2018). A lexicon-free approach for 3D handwriting recognition using classifier combination. Pattern Recognition Letters, 103, 1-7.
- [19]Kůrková, V., Manolopoulos, Y., Hammer, B., Iliadis, L., &Maglogiannis, I. (2018). Artificial Neural Networks and Machine Learning – ICANN 2018: 27th International Conference on Artificial Neural Networks, Rhodes, Greece, October 4-7, 2018, Proceedings. Basingstoke, England: Springer.
- [20]Larasati, R., &KeungLam, H. (2017, November). Handwritten digits recognition using ensemble neural networks and ensemble decision tree. In 2017 International Conference on Smart Cities, Automation & Intelligent Computing Systems (ICON-SONICS) (pp. 99-104). IEEE.
- [21]Lee, J. H., Shin, J., &Realff, M. J. (2018). Machine learning: Overview of the recent progresses and implications for the process systems engineeringfield. Computers & Chemical Engineering, 114,111-121.