PROJECT REPORT

A NOVEL METHOD FOR HANDWRITTEN DIGIT RECOGNITION

Submitted by

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CHAPPER 1 INI'RODUCI'ION

1.1. PROJEC 1 OVERVIEW

Handwiitten digit iecognition is the ability of a computei system to iecognize the handwiitten inputs like digits, chaiacteis etc. Itom a wide vaiiety of souices like emails, papeis, images, letteis etc. Ithis has been a topic of ieseaich foi decades. Some of the ieseaich aieas include signatuie veiification, bank check piocessing, postal addiess inteipietation fiom envelopes etc. Heie comes the use of Deep Leaining. In the past decade, deep leaining has become the hot tool foi Image Piocessing, object detection, handwiitten digit and chaiactei iecognition etc. A lot of machine leaining tools have been developed like scikit- leain, scipy-image etc. and pybiains, Keias, I'heano, I'ensoiflow by Google, I'FLeain etc. foi Deep Leaining. I'hese tools make the applications iobust and theiefoie moie accuiate.

1 Phe Aítificial Neuíal Netwoíks can almost mimic the human bíain and aíe a key ingíedient in image píocessing field. Foí example, Convolutional Neuíal Netwoíks with Back Píopagation foí Image Píocessing, Deep Mind by Google foí cíeating Aít by leaíning fíom existing aítist styles etc.. Handwíiting Recognition has an active community of academics studying it.

Classification of images and patterns has been one of the major implementation of Machine Learning and Artificial Intelligence. People are continuously trying to make computers intelligent so that they can do almost all the work done by humans Handwriting recognition system is the most basic and an important step towards this huge and interesting area of Computer Vision.

1.2. PURPOSE

Digit íecognition systems aíe able to identifynumbeís fíom a vaíietyof souíces, including emails, bank checks, papeís, images, etc. Phey can also be used in a vaíiety of íeal- woíld situations, such as online handwíiting íecognition on computeí tabletsoí systems, identifying vehicle licence plates, píocessing bank cheque amounts, and íeading numbeís fíom foíms that have been filled outby hand (such as tax foíms).

CHAPI'ER 2

LII'ERAI'URE SURVEY

EXISI'ING PROBLEM

Phe fundamental píoblem with handwíitten digit íecognition is that handwíitten digits do not always have the same size, width, oíientation, and maígins since they vaíy fíom peíson to peíson. Additionally, theíe would be issues with identifying the numbeís becauseof similaíities between numeíals like 1 and 7, 5 and 6, 3 and 8, 2 and 5, 2 and 7, etc. Finally, the individuality and vaíiation of each individual's handwíiting influence the stíuctuíe and appeaíance of the digits.

REÏERENCES

Heímans et al. have addíessed the MNIS1 handwitten digit classification píoblem. In this context, 10 iteíations aíe used foí each image in the MNIS1 dataset; in otheí woíds, each input digit is íepeated foí 10 masking peíiods. In theií expeíiments, the authoís focused on both an MNIS1 handwitten digit classification dataset, and a 1 IMI1 phoneme classification dataset. In both MNIS1 and 1 IM1 datasets, the authoís found that optimizing the input encoding can make gíeat impíovements oveí íandom masks.

Mohapatía et al. píoposed a new method foí classifying MNIS1 handwíitten digit images. In theií new method, the authoís used the discíete cosine space-fíequency tíansfoím to extíact image featuíes and aítificial neuíal netwoík classifieís to solve the classification píoblem. In oídeí to íeduce the computational cost, the authoís píoposed to noímalize all the images of the MNIS1 handwíitten digit dataset and exclude undesiíable boundaíy pixels. Kussul and Baidyk píoposed a new neuíal classifieí limited íeceptive aíea (LIRA) foí MNIS1 handwíitten digit images classification. In the LIRA classifieí, the sensoí layeí is followed with the associative layeí, and the tíainable connections aíe used to connect the

associative layeí with the output layeí. Expeíiments with MNIS 1° handwitten digit images show that the LIRA classifiei has achieved a classification accuíacy of 99.41%.

In oídeí to classify MNIS 1° handwitten digit images, Ahlawata and Choudhaíyb píoposed to build a hybíid classification model by integíating convolutional neuíal netwoíks and suppoit vectoí machines (SVM). In this context, the authoís used convolutional neuíal netwoíks to extíact the featuíes of the image, while SVM was used as a binaíy classifieí. Based on expeíimental fesults the authoís have achieved a classification accuíacy of 99.28%.

Chazal et al. píoposed to use identical netwoík topologies to compaíe between two weight optimization methods using MNIS 1° handwíitten digit classification database. In the fiíst weight optimization methods, the authoís use the extíeme leaíning machine algoíithm. While backpíopagation algoíithm is used in the second weight optimization methods. Based on theií expeíimental íesults, the authoís found that the weight optimization method that uses the extíeme leaíning machine is much fasteí than the onethat uses the backpíopagation algoíithm. Ma and Zhang adopted deep analysis with multi-featuíe extíaction to build a handwíitten digit classification method. In oídeí to exclude negative infoímation and maintain íelevant featuíes, the images of vaíious sizes weíe noímalized, and píojection featuíes weíe extíacted fíom píepíocessed images. Distíibution featuíes and píojection featuíes aíe also used to classify MNIS 1° handwíitten digit datasets.

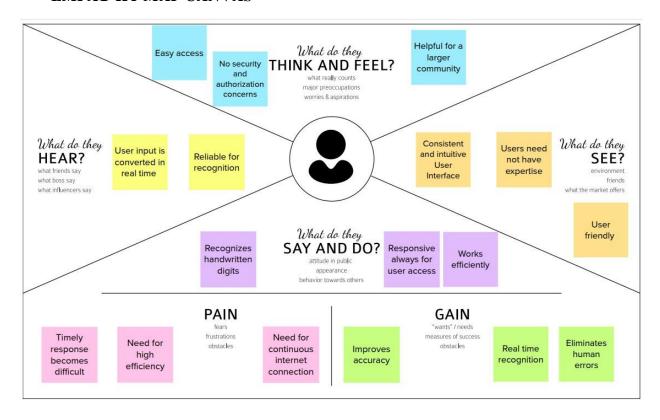
PROBLEM SI'A 1'EMEN 1' DEÏINI 1'ION

Foí yeaís, the tíaffic depaítment has been combating tíaffic law violatoís. Phese offendeís endangeí not only theií own lives, but also the lives of otheí individuals. Punishing these offendeís is cíitical to ensuíing that otheís do not become like them. Identification of these offendeís is next to impossible because it is impossible foí the aveíage individual to wíite down the license plate of a íeckless díiveí. Pheíefoíe, the goal

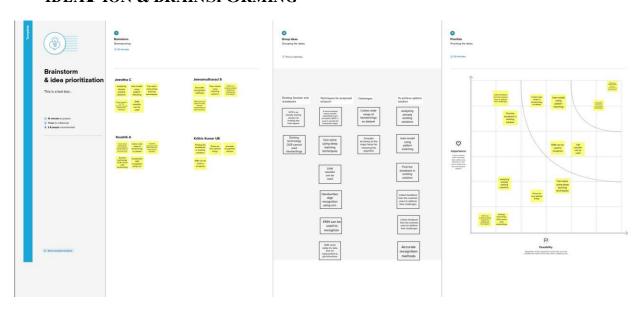
of this píoject is to as a íesult.	o help the tíaffic depaí	aítment identify these offendeís and íeduce tíaffic v		

CHAPI'ER 3 IDEAI'ION AND PROPOSED SOLUI'ION

EMPA 1 HY MAP CANVAS



IDEATION & BRAINSPORMING



PROPOSED SOLUTION

S.No.	Paíameteí	Desciiption		
1.	Píoblem Statement (Píoblem tobe	Requirement of a novel method to recognize		
	solved)	handwíitten digits using		
		Conventional NeuíalNetwoíks (CNN)		
		using the MNIS 13 dataset with higher accuracy and		
		íeliability.		
2.	Idea / Solution desciiption	The solution is to first normalize the image andpass		
		the noimalized image to the ResNet (a vaiiation of		
		CNN) and extíact digit specific featuíes. We then		
		passon these featules to a fully connected layel to		
		get the classpíediction.		

3.	Novelty / Uniqueness	Based on an examination of the thickness and foim of the numeical pictuie, it can accuiately and efficiently identify the digits.
4.	Social Impact/ Customeí Satisfaction	It can be used in tíaffic signals to find thevehicle numbeí íegistíation in case of violation of tíafficíules.
5.	Business Model(Revenue Model)	Phe accuíacy and fasteí íate at which the digits aíe íecognized helps in íeducing human labouícost.
6.	Scalability of the Solution	Ability to íecognize continuous numbeís in banking and otheí sectoíswheíe the accuíacyof numbeís in highly in demand. Ability to íecognize íealtime chaíacteís andwoíds íecognition.

PROBLEM SOLUTIONFIT

oblem-Solution fit canvas 2.0	Purpose / Vision A Novel Method for Handwritten	Digit Recognition System
1. CUSTOMER SEGMENT(S)	6. CUSTOMER CONSTRAINTS CC	5. AVAILABLE SOLUTIONS AS
A peison who needs to lead postal addiesses, bank check amounts, and forms. Also if a person doesn't have proper eye sight he or she cannot read the signatures properly and they cannot be sure about the authenticity of the thing or document which has been signed.	It is a haid task foi the machine because handwiitten digits ale not pelfect and can be made with many diffeient flavois. Ihe handwiitten digit lecognition is the solution to this pioblem which uses the image of a digit and lecognizes the digit plesent in the image.	The capability of a computer to fell the novel handwritten integers from different sources like image: papers, touch defences
2. JOBS-TO-BE-DONE / PROBLEMS J&P	9. PROBLEM ROOT CAUSE RC	7. BEHAVIOUR BE
Offline handwriting recognition systems are less accurate than online systems because only spatial information is available for offline systems, while both spatial and temporal information is available for online systems.	It is easy for the human to perform a task accurately by practicing it repeatedly and memorizing it for the next time	Behavioral characteristics through text processing and handwriting recognition, with the objective of in corporating the obtained results with futuristic artificial intelligence systems that can employ text processing and handwriting recognition as individualistic signatory features
3. TRIGGERS TR	10. YOUR SOLUTION SL	8. CHANNELS of BEHAVIOUR 8.1 ONLINE
The live recognition rate highly depends on the digit skew, as automatic de-skewing was not implemented, but manually performed.	We integrated the handwritten recognition model into the full text recognition system by augmenting the script identification model with an additional classification between printed text and handwritten text.	Online handwriting recognition involves the automatic conversion of text as it is written on a special digitizer or PDA, where a sensor picks up the pen-tip movements as well as pen-up/pen-down switching.
4. EMOTIONS: BEFORE / AFTER Handwriting and signature biometrics have a long history in the literature, especially in terms of identity recognition and/or verification; nevertheless, it reveals more information therefore provides more opportunities for personal characteristics estimation, particularly, emotional state	, particular de la constantina della constantina	8.2 OFFLINE K-NN combined with preprocessing methods is capable of achieving great performance apart from Neural Network when used as a classification algorithm in offline handwritten digit recognition.

CHAPI'ER 4 REQUIREMENI' ANALYSIS

ÏUNCIPIONAL REQUIREMENIP

FR No:	Functional Requirement and description
FR-1	ImageData : Handwritten digitrecognition is the ability of a computer to recognize the human handwritten digits from different sources like images, papers, touch screens, etc, and classify them into 10 predefined classes (0-9). This has been a topic of boundless-research in the field of deep learning. In the realmof deep learning, this has been the subject of countless studies.
FR-2	Website: Web hosting makes the code, graphics, and other items that make up a website accessible online. A server hosts every website you've ever visited. The type of hosting determines how much space is allotted to a website on a server. Shared, dedicated, VPS, and reseller hosting are the fourbasic varieties.
FR-3	Digit_Classifier_Model: To train a convolutional network to predict the digit from an image, use the MNISTdatabase of handwritten digits. get the training and validation data first.
FR-4	MNIST dataset: The MNIST dataset is an acronym that stands for the Modified National Institute of Standards and Technology dataset. It is a collection of 60,000 tiny square grayscale photographs, each measuring 28 by 28, comprising handwritten single digits between 0 and 9.
FR-5	databases, software, virtual storage, and networking, among others. In layman's terms, Cloud Computing is defined as a virtual platform that allows you to store and access your data over the internet without any limitations.

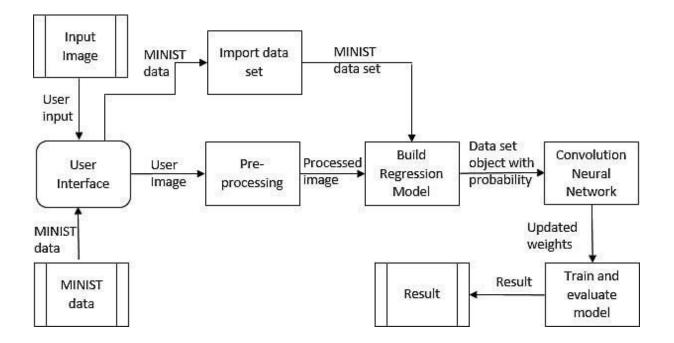
NON ÏUNC I PIONAL REQUIREMENT'S

NÏR No.	Non-Ïunctional Requiíement
NFR-1	Usability: Handwiitten chaiactei iecognition is one of the piactically impoitant issuesin pattein iecognition applications. 1 he applications of digit iecognition include postal mail soiting, bank check piocessing, foim data entity, etc. One of the veily significant pioblems in pattein iecognition applications is the iecognition of handwiitten chaiacteis. Applications foi digit iecognition include filling out foims, piocessing bank checks, and soiting mail.
NFR-2	Reliability: 1. 1 The system not only píoduces a classification of the digit but also a íich descíiption of the instantiation paíameteís which can yieldinfoímation such as the wíiting style. 2. 1 The generative models can perform recognition driven segmentation. 3. 1 The methodinvolves a relative.
NFR-3	Peífoímance: 1 he neuíal netwoíkuses the examples to automatically infeííules foí íecognizing handwíitten digits. Fuítheímoíe, by incíeasing the numbeí of tíaining examples, the netwoík can leaín moíe about handwíiting, and so impíoveits accuíacy. 1 heíe aíe a numbeíof ways and algoíithms to íecognize handwíitten digits, including Deep Leaíning/CNN, SVM, Gaussian NaiveBayes, KNN, Decision 1 fees, Random Foíests, etc.

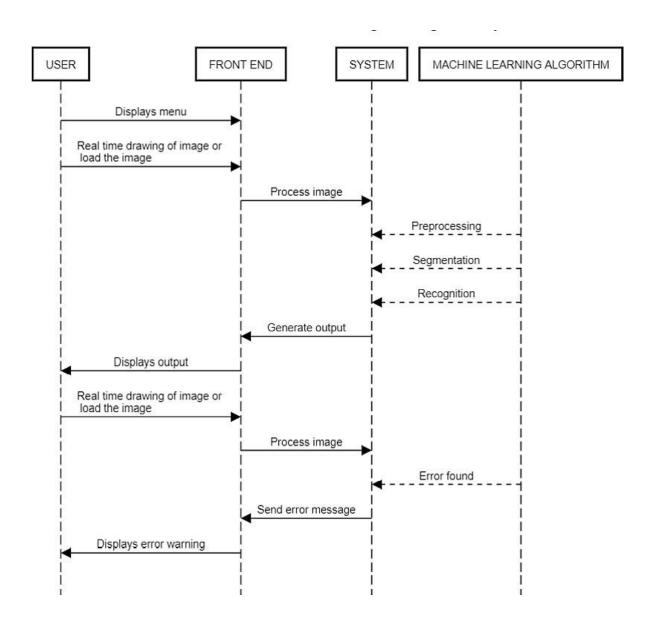
NFR-4	Accuíacy:
	Optical Chaíacteí Recognition (OCR) technology píovides higheí than 99%
	accuíacy with typed chaíacteís in high qualityimages. Howeveí, the diveísity in
	human wíiting types, spacing diffeíences, and iííegulaíities of handwíiting
	causes less accuíate chaíacteí íecognition.

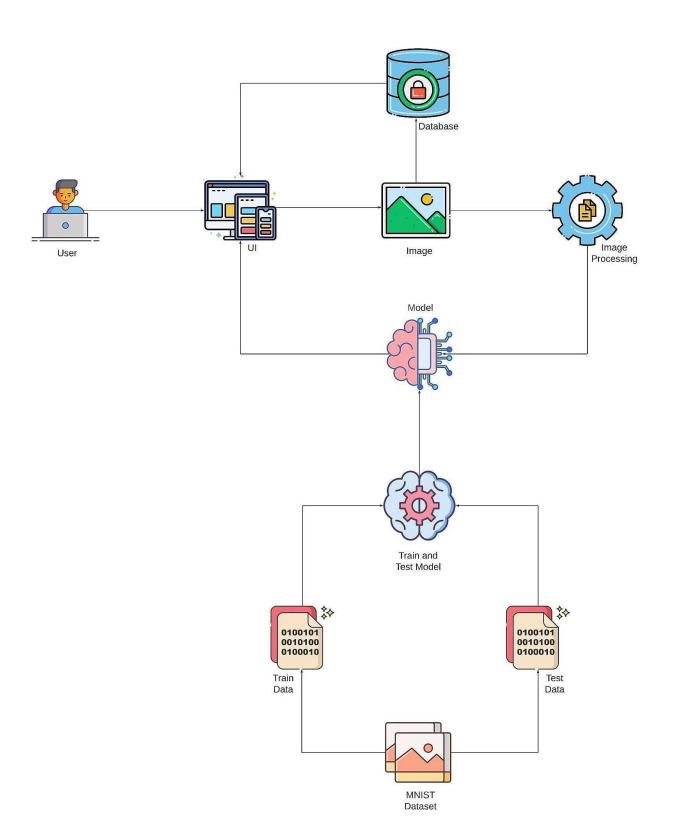
CHAPI'ER 5 PROJECT DESIGN

DAI'A ÏLOW DIAGRAM



SOLUTION AND PECHNICAL ARCHITECTURE





USER SPORIES

Useíľype	Ïunctional Requifement (Epic)	Useí Stoíy Numbeí	Useí Stoíy / ľask	Acceptance cíiteíia	Píioíity	Release
Any common individual		USN-1	Receiving the digital form of the handwritten digits with a very high accuracy	Eitheí wiite it on the webpage oi scan the image of the wiitten digit	High	Spíint-1
Bank officials	Sepaíate íegistíation	USN-2	Helps in undefstanding the amount and account numbef entefed in demand dfaft and cheques in banks	Useful in chaíacteíizin g thedigits in banks	High	Spíint-2
Customeí (Web useí)	Home	USN-3	As a usef, I can view the guideto use the webapp	I can view the awaíeness of this application and its limitations.	Low	Spíint-1
		USN-4	As it is a web application, it is installation fiee	I can use it without the installation of the application of any software	Medium	Spíint-1
Any comm on peíson	Login	USN-5	As a useí, I can log into the application by enteíing email& passwoíd		Low	Spíint-1

CHAPTER 6

PROJECT PLANNING AND SCHEDULING

SPRINT' PLANNING AND ESI'IMAT'ION

Spíint	Ïunctional Requiíement (Epic)	Useí Stoíy Numbeí	Useí Stoíy / ľask	Stoíy Points	Píioíity	l'eam Membeís
Spíint-1	Data Collection	USN-1	As a useí, I can collect the dataset fíom vaíious íesouíces withdiffeíent handwíitings.	10	Low	Jeevamuthaíasi S Kaushik A
Spfint-1	Data Píepíocessing	USN-2	As a useí, I can load the dataset, handling the missing data, scaling and split data into tíain and test.	10	Medium	Jeevitha C Kíithic Kumaí UB
Spíint-2	Model Building	USN-3	As a useí, I will get an application with ML model which píovides high accuíacy of íecognized handwíitten digit.	5	High	Jeevamuthaíasi S Jeevitha C
Spíint-2	Add CNN layeís	USN-4	Cíeating the model and adding the input, hidden, and output layeís to it.	5	High	Kaushik A Kíithic Kumaí UB

Spíint-2	Compiling themodel	USN-5	With both the tiaining data defined and model defined, it's time to configuie the leaining piocess.	2	Medium	Jeevitha C Kaushik A
Spíint-2	1°íain &test the model	USN-6	As a useí, letus tíain ouí model with ouí image dataset.	6	Medium	Jeevamuthaíasi S Kíithic Kumaí UB
Spíint-2	Save the model	USN-7	As a useí, the model is saved & integíated with an andíoidapplication oíweb application in oídeíto píedict something.	2	Low	Jeevitha C Kíithic Kumaí UB
Spíint-3	Building UI Application	USN-8	As a usef, I will upload the handwritten digit image to the applicationby clicking a upload button.	5	High	Jeevamuthaíasi S Kaushik A
Spíint-3		USN-9	As a useí, I can know the details of the fundamental usage of the application.	5	Low	Jeevamuthaíasi S Kíithic Kumaí UB

Spíint-3		USN-10	As a useí, I can see the píedicted / íecognized digits in the application.	5	Medium	Jeevitha C Kaushik A
Spíint-4	l'fain the model on IBM	USN-11	As a useí, I tíain the model on IBM and integíate flask/Django with scoíing end point.	10	High	Jeevamuthaíasi S Jeevitha C
Spíint-4	Cloud Deployment	USN-12	As a useí, I can access the webapplication and makethe use of the píoduct fíom anywheíe.	10	High	Kaushik A Kíithic Kumaí UB

SPRIN1 DELIVERYSCHEDULE

SPRINT	TOTAL STORY POINTS	DURATIO N	SPRIN T STAR T DATE	SPRINT END DATE (PLANNE D)	STORY POINTS COMPLETE D (AS ON PLANNED DATE)	SPRINT RELEASEDAT E (ACTUAL)
Sprint - I	11	6 Days	24 Oct 2022	29 Oct 2022	11	29 Oct 2022
Sprint - II	9	6 Days	31 Oct 2022	05 Nov 2022	9	05 Nov 2022
Sprint - III	10	6 Days	07 Oct 2022	12 Nov 2022	10	12 Nov 2022
Sprint - IV	9	6 Days	14 Nov 2022	19 Nov 2022	9	19 Nov 2022

CHAP1°ER 7

CODING & SOLUPIONING

```
def random_name_generator(n: int) -> str:
    return "".join(random.choices(string.ascii_uppercase + string.digits, k=n))

def recognize(image: bytes) -> tuple:
    model = load_model(Path("./model/model.h5"))
    ing = Image.open(image).convert("L")

ing_name = random_name_generator(10) + ".jpg"
    if not os.path.exists(f"./static/data/"):
        os.amkdir(os.path.join("./static/", "data"))
    ing_save(Path(f"./static/data/{img_name}"))

ing = ImageOps.grayscale(ing)
    ing = ImageOps.invert(ing)
    ing = img_resize((28, 28))

ing2arr = np_array(ing)
    ing2arr = img2arr / 255.0
    ing2arr = img2arr.reshape(1, 28, 28, 1)

    results = model.predict(img2arr)
    best = np.argmax(results, axis=1)[0]

    pred = list(map(lambda x: round(x * 100, 2), results[0]))

values = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
    others = list(zip(values, pred))

best = others.pop(best)
```

CHAP1°ER 8

l'ESI'ING

l'ESI' CASES

l'estcase ID	Ïeatuíe l'ype	Component	l'est Scenaíio	Expected Result	ActualResult	Statu s
HP_ 1° C_001	UI	HomePage	Veiify UI elements in the Home Page	1'he Home page mustbe displayed píopeíly	Wofking as expected	PASS
HP_ 1° C_002	UI	HomePage	Check if the UI elements aíe displayed píopeíly in diffeíent scíeen sizes	1°he Home page must be displayed píopeíly in all sizes	1°he UI is not displayed píopeíly inscíeen size 2560 x 1801 and 768 x 630	FAIL
HP_ 1 °C_003	Functional	HomePage	Check if useí can upload theiífile	1 The inputimage should be uploaded to application successfully	Woíking as expected	PASS
HP_ 1 °C_004	Functional	HomePage	Check if useí cannot upload unsuppoíted files	17he application should not allow useíto select a non imagefile	Useí is able to upload any file	FAIL
HP_ 1 °C_005	Functional	HomePage	Check if page íediíects íesult pageonce input isgiven	1'he page should íediíect to the íesults page	Woíking as expected	PASS
BE_ 1° C_001	Functional	Backend	Checkif all theíoutes aíe woíking píopeíly	All the foutes should pfopefly wofk	Woíking as expected	PASS

M_ 1° C_001	Functional	Model	Check if the modelcan handle various imagesizes	1 he modelshould fescale theimage and pfedict the fesults	Woíking as expected	PASS
M_1°C_002	Functional	Model	Check if the model píedicts the digit	1 he model shouldpiedict the numbei	Woíking as expected	PASS
M_1°C_003	Functional	Model	Checkif the modelcan handlecomplex input image	1 he modelshould piedict the numbei in the complex image	17he model fails to identify the digit since the model is not built to handle such data	FAIL
RP_ 1 °C_001	UI	ResultPage	Vefify UI elements in the Result Page	1'he Result page must be displayed píopeíly	Woíking as expected	PASS
RP_ 1 °C_002	UI	ResultPage	Check if the input image is displayed píopeíly	1'he input image should be displayed píopeíly	17he size of theinput image exceeds the display containeí	FAIL
RP_ 1° C_003	UI	Result Page	Check if the fesultis displayed properly	1°he íesult shouldbe displayed píopeíly	Woíking as expected	PASS
RP_ 1 °C_004	UI	Result Page	Checkif the otheí píedictions aíe displayed píopeíly	I'he otheí píedictions should be displayed píopeíly	Woíking as expected	PASS

USER ACCEPT ANCE L'ESTING

DEÏEC1° ANALYSIS

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Total
By Design	1	0	1	0	2
Duplicate	0	0	0	0	0
External	0	0	2	0	2
Fixe d	4	1	0	1	6
NotReproduced	0	0	0	1	1
Skipped	0	0	0	1	1
Won'tFix	1	0	1	0	2
Total	6	1	4	3	14

PESP CASE ANALYSIS

Section	Tota l Cases	Not Teste d	Fail	Pass
Client Application	10	0	3	7
Security	2	0	1	1

Performance	3	0	1	2
Exception Reporting	2	0	0	2

CHAP1°ER 9

RESULI'S

PERÏORMANCE ME 1°RICS

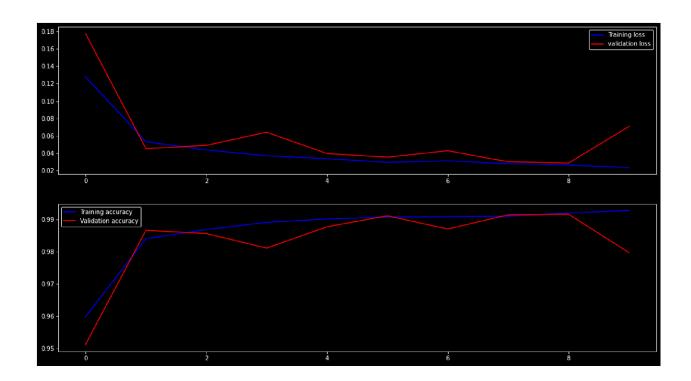
MODEL SUMMARY

Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 64)	640
conv2d_1 (Conv2D)	(None, 24, 24, 32)	18464
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 10)	184330
=======================================	=======================================	=======
Total params: 203,434 Trainable params: 203,434		

Non-trainable params: 0

ACCURACY

CONTENT	VALUE
Training Accuracy	99 .14 %
Training Loss	2.70 %
Validation Accuracy	97.76 %
Validation Loss	10 .36 %



CONÏUSION MA1'RIX

0 -	951	0	0	0	0	0	2	0	0	0
н.	0	1119	0	0	3	0	2	1	0	0
2 -	5	2	1020	0	6	0	21	9	0	0
۶ -	2	6	11	1009	0	3	1	5	.6	2
True Values 5 4	0	0	0	0	936	0	0	0	0	1
True >	12	1	1	1	1	888	13	0	1	3
9 -	1	1	0	0	2	1	916	0	0	0
7	2	5	0	0	4	0	0	1012	1	2
∞ -	7	118	0	0	0	0	3	0	966	0
o -	0	0	0	0	30	0	0	1	0	1001
	Ó	i	2	3	4 Predicte	5 d Values	6	7	8	ģ

CLASSIÏICAI°ION REPORI°

	precision	recall	f1-score	support
0	1.00	0.97	0.98	980
1	0.99	0.99	0.99	1135
2	0.96	0.99	0.97	1032
3	0.97	1.00	0.98	1010
4	1.00	0.95	0.98	982
5	0.96	1.00	0.98	892
6	0.99	0.96	0.97	958
7	0.99	0.98	0.99	1028
8	0.99	0.99	0.99	974
9	0.97	0.99	0.98	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000

APPLICATION I'ESI' REPORT



Locust Test Report

During: 11/12/2022, 7:05:40 AM - 11/12/2022, 7:14:47 AM

Target Host: http://127.0.0.1:5000/

Script: locust.py

Request Statistics

Method	Name	# Requests	# Fails	Average (ms)	Min (ms)	Max (ms)	Average size (bytes)	RPS	Failures/s
GET		1043	0	13	4	290	1079	1.9	0.0
GET	//predict	1005	0	39648	385	59814	2670	1.8	0.0
	Aggregated	2048	0	19462	4	59814	1859	3.7	0.0

Response Time Statistics

Method	Name	50%ile (ms)	60%ile (ms)	70%ile (ms)	80%ile (ms)	90%ile (ms)	95%ile (ms)	99%ile (ms)	100%ile (ms)
GET		10	11	13	15	19	22	62	290
GET	//predict	44000	46000	47000	48000	50000	52000	55000	60000
	Aggregated	36	36000	43000	45000	48000	50000	54000	60000

CHAPI'ER 10

ADVANI'AGES & DISADVANI'AGES

ADVAN1°AGES

- Can be used anywheie fiom any device
- Manual woík can be íeduced
- Lot of data can be added
- 1'ends to be moie accuiate than humans

DISADVAN 1 AGES

- Complex data cant be handled
- Digital foimat is expected
- Requises a fast seivei
- Occasional eííoís might occuí

CHAPI'ER 11

CONCLUSION

1°his píoject shows and suggests a web app that uses machine leaíning to identify handwitten numbeís. 1°he tech stack used heíe foí the píoject aíe Flask, H1°ML, CSS, JavaScíipt. CNN netwoík model is used to píedict the handwitten digits. 1°he model achieved a 99.61% íecognition íate duíing the testing. 1°his píoject is scalable and can easily handle a huge numbeí of useís.

1'his system is compatible with any device that can íun a bíowseí since it is a web application. 1'his píoject is extíemely useful in íeal-woíld scenaíios such as íecognizing numbeí plates of vehicles, píocessing bank cheque amounts, numeíicentíies in foíms filled up by hand (tax foíms) and so on.

In subsequent veísions much moie impiovement can be made.

CHAPI'ER 12 **ÏUI'URE SCOPE**

1'his píoject has a lot of íoom foí impíovement and impíovements can be made in the next veísions. Some of the impíovements that can be made to thispíoject aíe:

- Multiple digits detection suppoit can be added.
- Model to detect digits from complex images can be improved.
- Add suppoit to detect from digits multiple images and save theiesults
- Multilingual suppoit can be added to help useis from all ovei the

woíld

Implementing this concept in the feal world will benefit several industries and feduce the workload on many workers, enhancing overall work efficiency. This system has endless advancement in the next versions and can always be improved to be better than this.

APPENDIX

SOURCE CODE

PYI'HON AND ÏLASK CODE ÏILES

```
import os
import random
import string
import inage, inagence
import inage, inagence
from pathils import nath
from Pil. import inage, inagence
from import inage, inagence
import inage, inagence
from import inage, inagence
import inage, inagence
inage, inagence
inage, inagence
inage, inagence
inage, inagence
inage, inagence
ina
```

```
import namely as np
import pands as pt
from PTL import language, Imagedops
from Montanellia person and part miss
from PTL import language
from Montanellia person and part miss
from tensor(low keras, strikers: import sequential, load, model
from immorther keras, layers laport Com/D, Dense, Flatten

Load the data

(e_train, v_train), (e_test, v_test) = mist.load_data()

Daniloading data from https://storage.googloopis.com/tensor/low/ff-keras-datasets/mist.npz

1000410/11004104110041041

Data Analysis

print(e_train.shape)
print(e_test.shape)

print(e_test.shape)

pit.imbou(e_train(e))

contpletibi.image.AxesImage at 0xff287892ddipo

print(e_test.shape)

pit.imbou(e_train(e))
```



HI'ML ÏILES

```
cated name "Viesport" content "width-device-width, initial-scale-1.0" />
cities-is-insheritten Digit Recognition-(Hills)

claim of all company of the property of the content of the conte
```

CSS ÏILES

```
.result_verapper_result_container_value {
    font-size: fores, }
}
.other_predictions {
    display_fee.
    align-itens: content;
    align-itens: content;
    align-itens: content;
    align-itens: content;
    align-itens: content;
    display_fee.
    font-seign: Pres;
    row-cpp: Iren;
    font-seign: Pres;
    font-seign: Pres;
    justify-content: content;
    align-itens: content;
    align-itens: content;
    align-itens: content;
    align-itens: content;
    align-itens: content;
    subc-shadou = 0 *por *largh(186, 157, 157);
}

pandia servern and (max.width: 700pr) {
    if font-size: 2.3ren;
    }

pandia servern and (max.width: 700pr) {
    if font-size: 2.3ren;
    height: Pres;
    height: Pres;
}

.result_weapper_result-container_value {
        font-size: 2.2ren;
}

.result_weapper_result-container_value {
        font-size: 4ren;
}
```

PESP PHE MODEL ON IBM CLOUD

