HANDWRITTEN DIGIT RECOGNITION USING DEEP LEARNING

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ABSTRACT

Handwritten digit recognition is gaining a huge demand in the branch of computer vision. We are going to implement a better and accurate approach to perceive and foresee manually written digits from 0 to 9. A class of multilayer sustain forward system called Convolutional network is taken into consideration. A Convolutional network has a benefit over other Artificial Neural networks in extracting and utilizing the features data, enhancing the knowledge of 2D shapes with higher degree of accuracy and unvarying to translation,scaling and other distortions. The LeNet engineering was initially presented by LeCun et al in their paper.The creators excecution of LeNet was primarily focused on digit and character recognition.LeNet engineering is clear and simple making it easy for implementation of CNN's. We are going to take the MNIST dataset for training and recognition.

The primary aim of this dataset is to classify the handwritten digits 0-9 . We have a total of 70,000 images for training and testing. Each digit is represented as a 28 by 28 grey scale pixel intensities for better results. The digits are passed into input layers of LeNet and then into the hidden layers which contain two sets of convolutional,activation and pooling layers. Then finally it is mapped onto the fully connected layer and given a softmax classifier to classify the digits.We are going to implement this network using keras deep learning inbuilt python library

1. INTRODUCTION

Handwriting recognition is the ability of a machine to receive and interpret handwritten input from multiple sources like paper documents, photographs, touch screen devices etc. Recognition of handwritten and machine characters is an emerging area of research and finds extensive applications in banks, offices and industries. The main aim of this project is to design expert system for**, HANDWRITTEN DIGIT RECOGNITION USING DEEP LEARNING** that can effectively recognize a particular character of type format using the Artificial Neural Network approach.

Neural computing Is comparatively new field, and design components are therefore less well specified than those of other architectures. Neural computers implement data par- allelism. Neural computer are operated in way which is completely different from the oper- ation of normal computers.

Project Definition

This application is useful for recognizing all character (digits) given as in input image. Once input image of character is given to proposed system, then it will recognize input character which is given in image. Recognition and classification of characters are done by Neural Network. The main aim of this project is to effectively recognize a particular character of type format using the Artificial Neural Network approach.

Relevant Theory

Benefits of Digiti Recognition :

1.In forensic application Handwritten digit recognition will be an effective method for evidence collection.

2.It will also help to reduce noise from the original character.

3.Our method develop accuracy in recognizing character in divert font and size.

4.More set of sample invites more accuracy rate because of heavy training and testing session.

What is Neural Network

An Artificial Neural Network (ANN) is an information-processing paradigm that is in- spired by the way biological nervous systems, such as the brain, process information.The key element of this paradigm is the novel structure of the information processing system. It is composed of large no. of highly interconnected processing element (neurons) working in union to solve specific problems. Learning in a Biological system involves adjustments to the synaptic connections that exist between the neuron.Handwritten digit dataset are vague in nature because there may not always be sharp and perfectly straight lines. The main goal in digit recognition is feature extraction is to remove the redundancy from the data and gain a more effective embodiment of the word image through a set of numerical attributes. It deals with extracting most of the essential information from image raw data [6]. In addition the curves are not necessarily smooth like the printed characters. Furthermore, characters dataset can be drawn in different sizes and the orientation which are always supposed to be written on a guideline in an upright or downright point. Accordingly, an efficient handwritten recognition system can be developed by considering these limitations. It is quiet exhausting that sometimes to identify hand written characters as it can be seen that most of the human beings can't even recognize their own written scripts. Hence, there exists constraint for a writer to write apparently for recognition of handwritten documents.

Before revealing the method used in conducting this research, software engineering module is first presented. Pattern recognition along with Image processing plays compelling role in the area of handwritten character recognition. The study [7], describes numerous types of classification of feature extraction techniques like structural feature based methods, statistical feature based methods and global transformation techniques. Statistical approaches are established on planning of how data are selected. It utilizes the information of the statistical distribution of pixels in the image. The paper [8], provided SVM based offline handwritten digit recognition system. Authors claim that SVM outperforms in the experiment. Experiment is carried out on NIST SD19 standard dataset. The study [9] provide the conversion of handwritten data into electronic data, nature of handwritten characters and the neural network approach to form machine competent of recognizing hand written characters. The study [10] addresses a comprehensive criterion of handwritten digit recognition with various state of the art approaches, feature representations, and datasets. However, the relationship of training set size versus accuracy/error and the dataset-independence of the trained models are analyzed. The presents convolution neural networks into the handwritten digit recognition research and describes a system which can still be considered state of the art.

2. LITERATURE SURVEY AND RELATED WORK

CNN is playing an important role in many sectors like image processing. It has a powerful impact on many fields. Even, in nano-technologies like manufacturing semiconductors, CNN is used for fault detection and classification. Handwritten digit recognition has become an issue of interest among researchers. There are a large number of papers and articles are being published these days about this topic. In research, it is shown that Deep Learning algorithm like multilayer CNN using Keras with Theano and Tensorflow gives the highest accuracy in comparison with the most widely used machine learning algorithms like SVM, KNN & RFC. Because of its highest accuracy, Convolutional Neural Network (CNN) is being used on a large scale in image classification, video analysis, etc. Many researchers are trying to make sentiment recognition in a sentence. CNN is being used in natural language processing and sentiment recognition by varying different parameters. It is pretty challenging to get a good performance as more parameters are needed for the large-scale neural network. Many researchers are trying to increase the accuracy with less error in CNN. In another research, they have shown that deep nets perform better when they are trained by simple back- propagation. Their architecture results in the lowest error rate on MNIST compare to NORB and CIFAR10. Researchers are working on this issue to reduce the error rate as much as possible in handwriting recognition. In one research, an error rate of 1.19% is achieved using 3-NN trained and tested on MNIST. Deep CNN can be adjustable with the input image noise. Coherence recurrent convolutional network (CRCN) is a multimodal neural architecture. It is being used in recovering sentences in an image. Some researchers are trying to come up with new techniques to avoid drawbacks of traditional convolutional layer's. Ncfm (No combination of feature maps) is a technique which can be applied for better performance using MNIST datasets. Its accuracy is 99.81% and it can be applied for largescale data. New applications of CNN are developing day by day with many kinds of research. Researchers are trying hard to minimize error rates. Using MNIST datasets and CIFAR, error rates are being observed. To clean blur images CNN is being used. For this purpose, a new model was proposed using MNIST dataset. This approach reaches an accuracy of 98% and loss range 0.1% to 8.5%. In Germany, a traffic sign recognition model of CNN is suggested. It proposed a faster performance with 99.65% accuracy. Loss function was designed, which is applicable for light- weighted 1D and 2D CNN. In this case, the accuracies were 93% and 91% respectively

K- nearest neighbor classifier:

A KNN classifier with a distance measure like Euclidean distance between the data sets input images is also capable of classification of digits but at higher error rate than a fully connected ML neural network. The key features of this classifier is that it requires no training time and no input from the programmer in terms of knowledge for designing the system. The big over head of this classifier is memory requirement and the classification or recognition time. We take into consideration that this nearest-neighbor system works on raw pixels instead of feature vectors

KNN is the non-parametric method or classifier used for classification as well as regression problems. This isthe lazy or late learning classification algorithm where all of the computations are derived until the last stageof classification, as well as this, is the instance-based learning algorithms where the approximation takes place locally. Being simplest and easiest to implement there is no explicit training phase earlier and the algorithm does not perform any generalization of training data.

Fully connected Multi-Layer Neural Network:

A Multi-Layer Neural Network with one or more number of hidden units is capable of classifying the digits in MNIST data set with a less than 2 % error rate on test set.This network extracts features based on the entire spatial domain of images hence the number of parameters required is very high. The problem with these networks is they tend to be over parameterized, in order of 100,000's which is unwanted when working with complex classification problems with complex data sets.

One way of thinking about fully connected networks is that each fully connected layer effects a transformation of the feature space in which the problem resides. The idea of transforming the representationof a problem to render it more malleable is a very old one in engineering and physics. It follows that deep learning methods are sometimes called –representation learning.‖ (An interesting factoid is that one of the major conferences for deep learning is called the –International Conference on Learning Representations.‖)

Handwritten Digit Recognition Using Machine Learning:

As using machine learning algorithms are used like KNN, SVM, Neural networks along with different parameters and feature scaling vectors, we also saw the different comparison among the classifiers in terms of the most important feature of accuracy and timing. Accuracy can alter as it depends on the splitting of training and testing data, and this can further be improved if the number of training and testing data is provided. There is always a chance to improve accuracy if the size of data increases. Every classifier has its own accuracy and time consumption. We can also include the fact that if the power of CPU changes to GPU,the classifier can perform with better accuracy and less time and better results can be observed.

The performance of the classifier can be measured in terms of ability to identify a condition properly (sensitivity), the proportion of true results (accuracy), number of positive results from the procedure of classification as false positives (positive predictions) and ability to exclude condition correctly (specificity).In this, we saw a brief comparison to the classifiers of Machine learning and deep learning.

Till now, the algorithms of Deep learning have performed better in the application of Handwritten DigitRecognition.

3. EXISTING SYSTEM

Handwritten digit recognition using deep learning has made significant advancements in recent years, and several existing systems have been developed to achieve high accuracy in this task. One popular dataset used for benchmarking handwritten digit recognition is the MNIST dataset, which consists of 28x28 pixel grayscale images of handwritten digits (0-9). Here's an overview of the components and techniques commonly found in existing systems for handwritten digit recognition:

1. Data Preprocessing:

-Data Augmentation: To improve model generalization, data augmentation techniques like rotation, scaling, and translation may be applied to generate additional training samples.

-Normalization: Images are typically scaled to have pixel values between 0 and 1 to help with model convergence.

2. Deep Learning Models:

-Convolutional Neural Networks (CNNs): CNNs are the most commonly used architecture for handwritten digit recognition. They are effective at capturing spatial hierarchies and local patterns within the images.

Recurrent Neural Networks (RNNs): Some systems use RNNs, particularly for recognizing sequences of digits, such as in address recognition on envelopes.

3. Model Architecture:

-Convolutional Layers: These layers extract features from the input images through convolutional filters.

-Pooling Layers: Pooling layers downsample feature maps to reduce computational complexity.

-Fully Connected Layers: These layers are typically used for classification after extracting features with convolutional layers.

4. Loss Function:

-Cross-Entropy Loss: The cross-entropy loss is commonly used for classification tasks like handwritten digit recognition.

5. Optimization Algorithms:

-Stochastic Gradient Descent (SGD): SGD and its variants like Adam are often used for training deep learning models.

6. Regularization:

-Dropout: Dropout layers are used to prevent overfitting.

-L2 Regularization: L2 regularization is applied to the model's weights.

7. Hyperparameter Tuning:

- Grid search or random search is used to find optimal hyperparameters like learning rate, batch size, and the number of layers and units.

8. Evaluation Metrics:

- Common evaluation metrics include accuracy, precision, recall, and F1-score.

9. Deployment:

- Models can be deployed on various platforms, including web applications, mobile apps, and embedded devices, to recognize handwritten digits in real-time.

10.State-of-the-Art Architectures:

- Researchers have developed advanced architectures like ResNet, DenseNet, and EfficientNet, which have achieved impressive results on handwritten digit recognition tasks.

11. Ensemble Methods:

- Combining multiple models through ensemble methods, such as bagging or boosting, can further improve recognition accuracy.

12. Transfer Learning:

- Pre-trained models on large datasets (e.g., ImageNet) can be fine-tuned for handwritten digit recognition to leverage their feature extraction capabilities.

13. Online Recognition:

- For applications like digit recognition on tablets or touchscreen devices, online recognition techniques, which analyze the trajectory of the written digit, can be used.

14. Continuous Learning:

- In scenarios where the model needs to adapt to new handwriting styles over time, continual or online learning approaches may be employed.

15. Post-processing:

- Post-processing techniques can be applied to correct errors and improve recognition accuracy, such as using language models to validate sequences of digits.

Many existing systems combine these components and techniques to build accurate and efficient handwritten digit recognition systems, which have applications in areas like postal services, banking, and digitized document processing. State-of-the-art systems continue to push the boundaries of accuracy and robustness in this field.

4. PROPOSED SYSTEM

A proposed system for handwritten digit recognition using deep learning would incorporate modern techniques and technologies to achieve high accuracy and robustness in recognizing handwritten digits. Here's an outline of such a system:

1. Data Collection and Preprocessing:

- Collect a diverse dataset of handwritten digits, including a wide range of handwriting styles, sizes, and orientations.

- Preprocess the data by resizing all images to a uniform size (e.g., 28x28 pixels) and normalizing pixel values to a specific range (e.g., [0, 1]).

2. Data Augmentation:

- Apply data augmentation techniques to increase the size of the training dataset. Techniques may include random rotations, translations, and variations in brightness and contrast.

3. Model Architecture:

- Use a Convolutional Neural Network (CNN) architecture, which has proven to be highly effective for image-based tasks like handwritten digit recognition.

- Consider using more advanced architectures like ResNet or EfficientNet, which may provide better performance.

4. Model Training:

- Split the dataset into training, validation, and testing sets.

- Train the CNN model on the training data using an appropriate loss function (e.g., cross-entropy) and an optimization algorithm (e.g., Adam).

- Implement techniques like dropout and batch normalization to prevent overfitting.

5. Hyperparameter Tuning:

- Perform hyperparameter tuning using methods like grid search or random search to find the optimal learning rate, batch size, and model architecture.

6. Ensemble Learning:

- Experiment with ensemble methods to combine multiple models' predictions to improve accuracy. Techniques like bagging or boosting can be considered.

7. Documentation and User Support:

- Provide thorough documentation for system users and offer user support to assist with any issues or inquiries.

8. Monitoring and Logging:

- Implement monitoring and logging mechanisms to track system performance and user interactions for further improvements.

By incorporating these elements into your proposed system, you can create a robust and accurate handwritten digit recognition system using deep learning that can be applied to a wide range of applications, from digitizing documents to enhancing user interfaces in various domains.

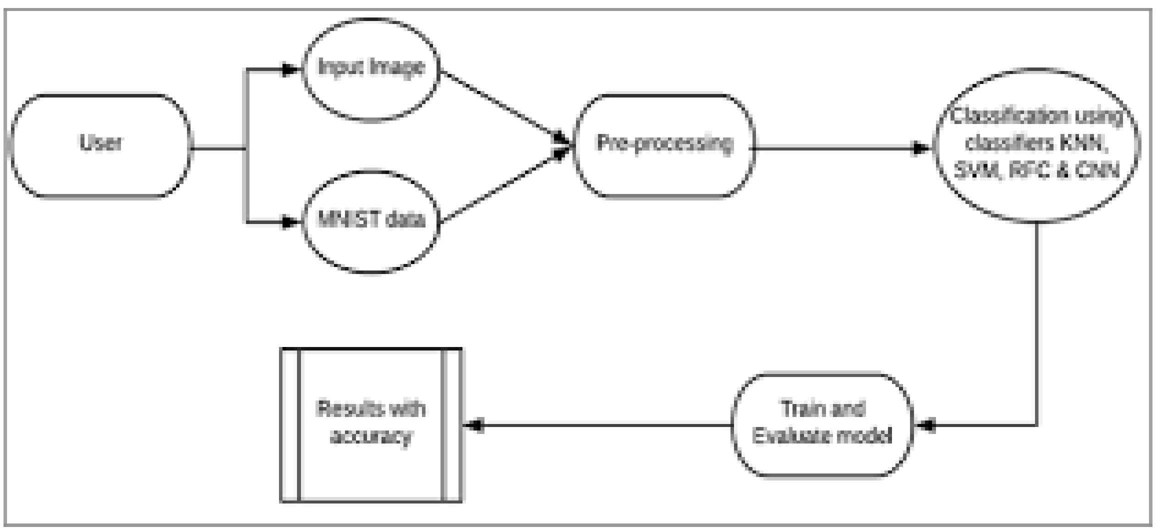

FIG1- SYSTEM ARCHITECTURE

5. METHODOLOGIES

MODULE

Convolutional Neural Network (CNN):

A simple CNN model can be seen in Fig. 1. The first layer is the input layer; the size of the input image is 28 × 28. The second layer is the convolution layer C2, it can obtain four different feature maps by convolution with the input image. The third layer is the pooling layer P3. It computes the local average or maximum of the input feature maps. The next convolution layer and pooling layer operate in the same way, except the number and size of convolution kernels. The output layer is full connection; the maximum value of output neurons is the result of the classifier in end. A simple structure of CNN.

Convolutional Neural Network (CNN):

Deep Neural Network (DNN):

The initially random weights of DNN are iteratively trained to minimize the classification error on a set of labeled training images; generalization performance is then tested on a separate set of test images. DNN has 2-dimensional layers of winner-take-all neurons with overlapping receptive fields whose weights are shared. Given some input pattern, a simple max pooling technique determines winning neurons by partitioning layers into quadratic regions of local inhibition, and selecting the most active neuron of each region. The winners of some layer represent a smaller, down-sampled layer with lower resolution, feeding the next layer in the hierarchy. The approach is inspired by Hubel and Wiesel's seminal work on the cat's primary visual cortex, which identified orientation selective simple cells with overlapping local receptive fields and complex cells performing downsampling-like operations is shown in.‖ The structure of DNN . D. Neural Network Toolbox in matlab (simulate): Neural Network Toolbox provides algorithms, functions, and apps to create, train, visualize, and simulate neural networks. The toolbox includes convolutional neural network and auto encoder deep learning algorithms for image classification and feature learning tasks by used MATLAB programming language. **Convolutional Neural Network (CNN):**
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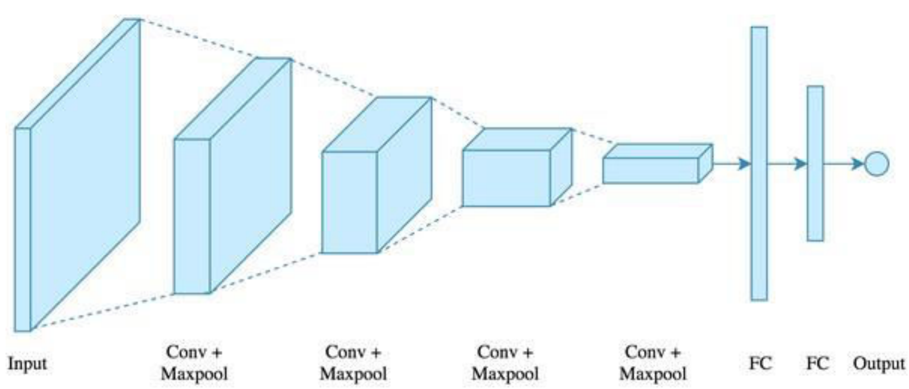

Fig 2- Convolutional Neural Network (CNN):

Deep Neural Network (DNN):

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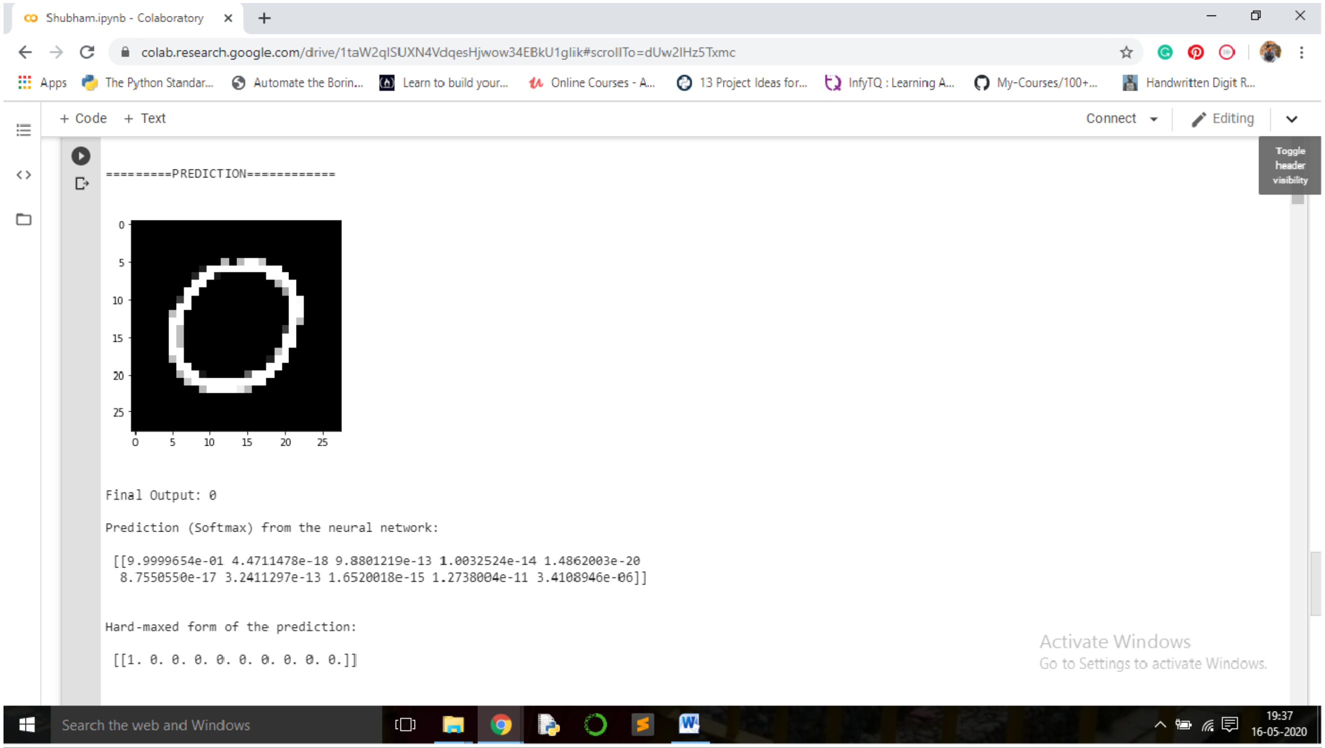

6. RESULTS AND DISCUSSION SCREEN SHOTS

FIG -3 Output 1

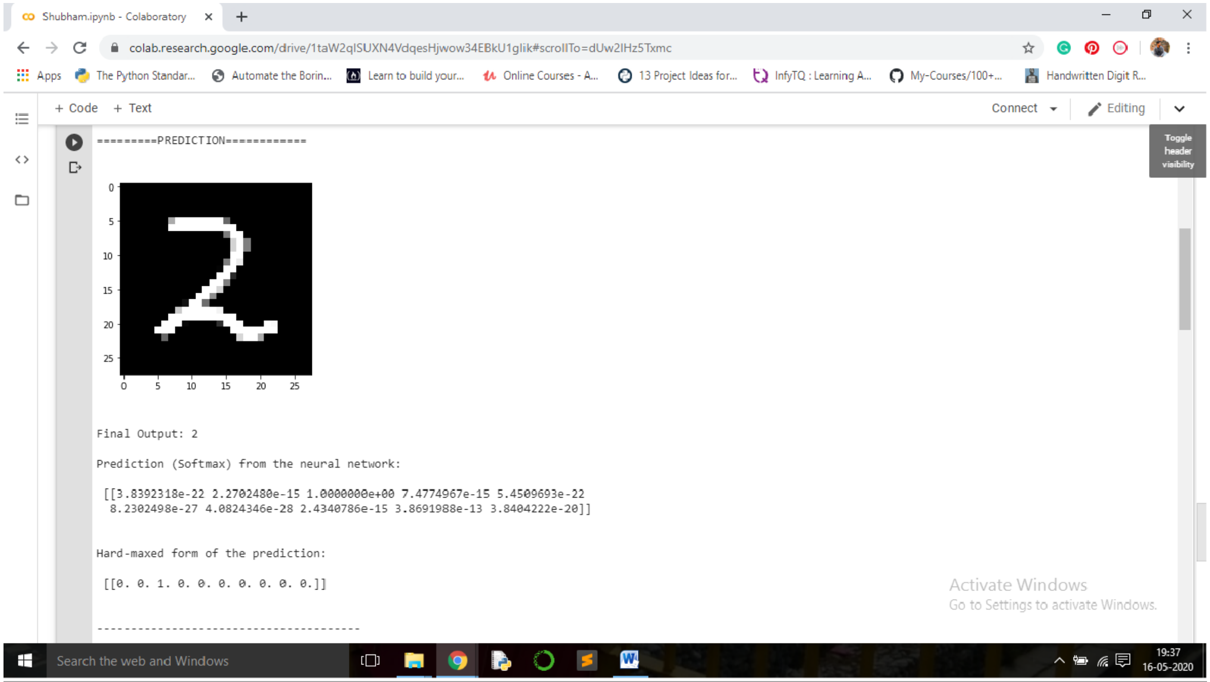

Fig 4-Output 2

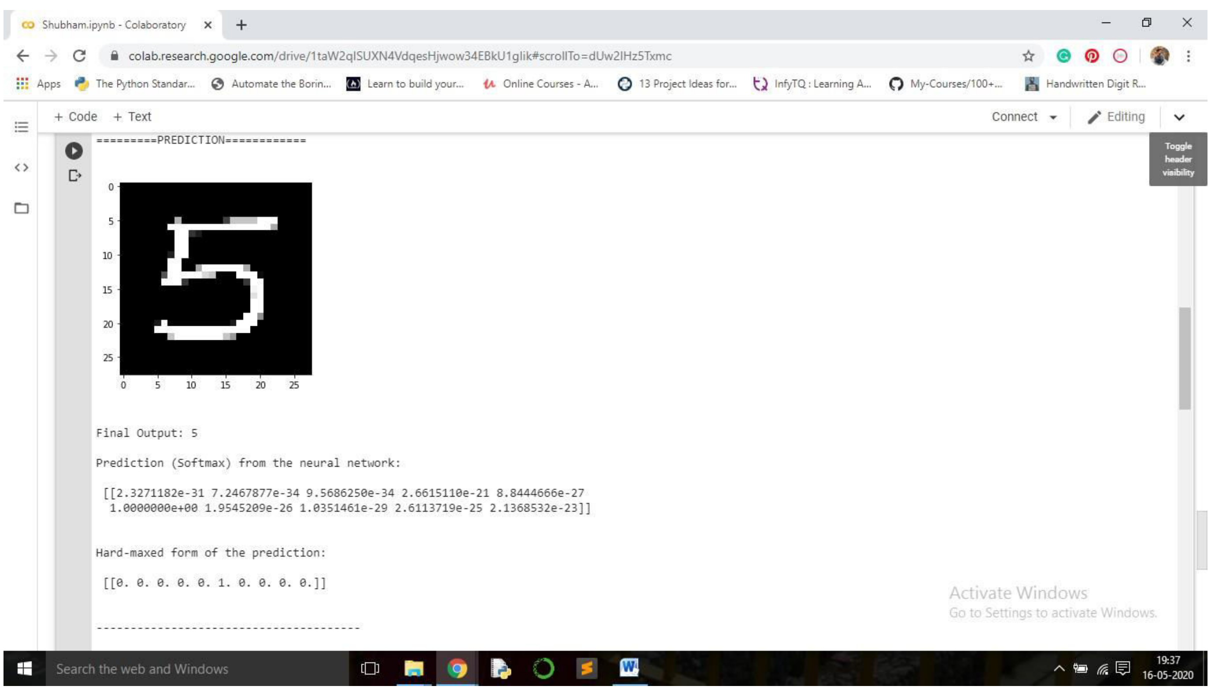

Fig 5 - Output 3

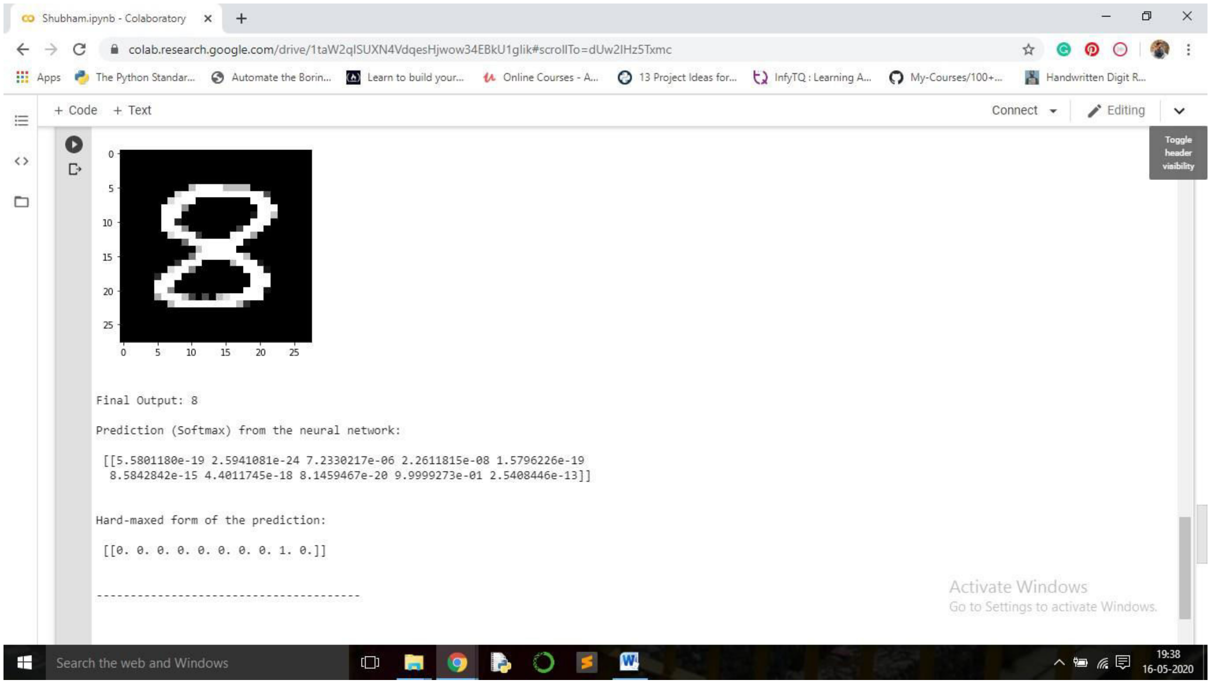

Fig 6- Output 4

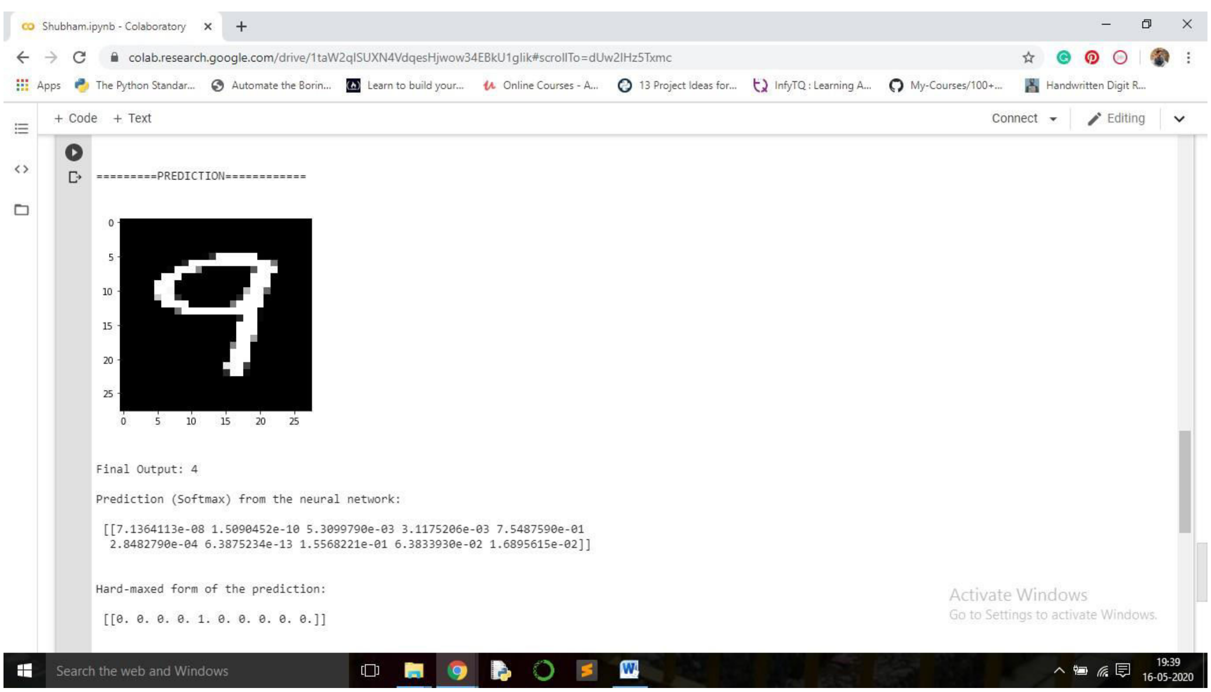

Fig 7- Output 5

7. CONCLUSION AND FUTURE SCOPE

Conclusion

In this study, interdisciplinary research has been carried out for Handwritten Digit Prediction through interaction of 60,000 sample dataset. A robust multilayer prediction model is generated in combination with the computation of maximum obtainable seismic features. 36 seismic features are consider for this problem. The features are employed for training of an earthquake prediction model for better result. The prediction model consists of Random forests classifier (RFC) method. RFC provides an initial estimation for Handwritten Digit prediction. Thus RFC based prediction model is trained and tested successfully with encouraging and improved result by selecting important features and training model. Performance of a network depends on many factors like low memory requirements, low run time and better accuracy, although in this paper it is primarily focused on getting better accuracy rate for classification. Before Artificial neurons had better accuracy but now the branch of computer vision mainly depends on deep learning features like convolutional neural networks. The branch of computer vision in artificial intelligence primary motive is to develop a network which is better to every performance measure and provide results for all kinds of datasets which can be trained and trained and recognized.

Future scope

"Future scope testing" is not a recognized term in software testing. However, I can provide you with some insights into the potential future directions and areas of advancement in the field of handwritten digit recognition using deep learning:

1. Improved Models: Future developments may focus on creating more sophisticated neural network architectures specifically tailored for handwritten digit recognition. This could involve exploring novel network architectures, attention mechanisms, or advanced recurrent networks.

2. Transfer Learning: Leveraging pre-trained models on large datasets for other computer vision tasks and fine-tuning them for handwritten digit recognition can become more common. Transfer learning can reduce the need for large labeled datasets.

3. Data Augmentation: Researchers may continue to explore advanced data augmentation techniques to artificially expand the training dataset. These techniques can improve model robustness and generalization.

4. Semi-Supervised and Unsupervised Learning: Research in semi-supervised and unsupervised learning methods for handwritten digit recognition may yield models that require less labeled data while maintaining high accuracy.

5. Multimodal Recognition: Integrating multiple sources of information, such as textual descriptions or audio input, alongside images of handwritten digits, could open up new applications and research areas.

6. Enhanced Preprocessing: Future preprocessing techniques may involve more advanced methods for noise reduction, image segmentation, and feature extraction, leading to improved model performance.

7. Real-Time Recognition: Advancements in hardware and software may enable real-time handwritten digit recognition on various platforms, including mobile devices and embedded systems.

8. Interpretable Models: Developing interpretable deep learning models for handwritten digit recognition can enhance model transparency and trustworthiness, making them more suitable for critical applications.

9. Security and Adversarial Robustness: Researchers may focus on making recognition systems more secure against adversarial attacks, where attackers manipulate input to deceive the model.

10. Human-AI Collaboration: Exploring ways in which deep learning models can work alongside humans in tasks like digit recognition, providing assistance and enhancing human productivity.

11. Deployment in New Domains: Applying handwritten digit recognition techniques to new domains beyond traditional character recognition, such as recognizing handwritten mathematical equations, diagrams, or historical documents.

12. Continuous Learning: Developing models that can learn continuously from new data without forgetting previous knowledge. This is particularly important for recognizing evolving handwriting styles.

13. Privacy-Preserving Techniques: Research into techniques that protect the privacy of handwritten data while still enabling accurate recognition, particularly in sensitive applications like healthcare.

14. Globalization and Multilingual Recognition: Extending recognition systems to work with multiple languages and scripts, accommodating a broader range of users and documents.

15. Benchmark Datasets: The creation of new, challenging benchmark datasets for handwritten digit recognition can drive further research and enable fair comparisons between different models.

As the field of deep learning and handwriting recognition continues to advance, there will likely be numerous opportunities for testing, validation, and verification of these new technologies to ensure their reliability and accuracy in various applications.

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