

A New Approach for Turning Handwritten Text into Digitalized Text Using DNN in Real Complex Scenarios

Dr. R. Josphineleela R.¹, Yogashree G. S.², Monisha G. S.³

¹Professor, Dept. of CSE Panimalar Engineering College Poonamallee, Chennai, India.

Pitleela2016@gmail.com

²PG Scholar, Panimalar Engineering College Poonamallee, Chennai, India.

yogashree24@gmail.com

³Associate Professor, Dept. of CSE Panimalar Engineering College
poonamallee, Chennai, India.

gsmonisha30@gmail.com

Article Info

Page Number: 1777 – 1796

Publication Issue:

Vol. 71 No. 3s2 (2022)

Article History

Article Received: 22 April 2022

Revised: 10 May 2022

Accepted: 15 June 2022

Publication: 19 July 2022

Abstract. Human handwritten character recognition plays a significant role in many public and private sectors, including banking, medicine, and education. Many studies have been conducted on hand-written text recognition to ensure that stroke edges of each character can be accurately recognized. Even though a number of technologies are available to recognize characters, none provide effective recognition of stroke edges. To overcome this problem, Deep Neural Network (DNN) is used as a methodology to identify the edges of the character, so as to convert the handwritten character into a human-readable form. The major challenge is to recognize the edges of each character with a high degree of accuracy. The recognition process is extremely accurate and efficient in identifying the stroke of the handwritten character. According to the overall performance of the proposed approach, it proves to be most efficient in giving a benchmark as well as flexible in conversion with much less time constraint.

Keywords- Hand written, text, public sectors, Deep neural network, accuracy, stroke edges, performance.

1.INTRODUCTION

During the current globalization, Handwritten to Text Recognition is becoming increasingly popular. This is capable of handwriting recognition describe the ability of the computer to translate the human writing character into text format. The character structure is identified using the [10] traditional Optical Character Recognition (OCR). The ability to recognize handwritten characters plays a major role in the world of technology, lowering the cost of storing information. It enhances the role in the medical field and many other banking sectors. Handwriting [11] numerous favorable variables have resulted in recognition's rapid development in the current innovation globe. There are a variety of advancements that will allow others to profit from the handwriting character. This works by having people write letters in a different style and allowing the computer to recognize the suggested letter and convert it to a book archive.

Generally, detecting the text lines in degraded historical document images is the most

complex process. The strategy pursues a traditional two-advance system wherein the binarization is first performed and after that, the content lines are separated from the twofold picture. So as to address the [7] difficulties in recorded archives, for example, report corruption, commotion in the structure, and slants. The fundamental content square is separated and the slanted point and composing style are compensated. Experiments are performed on various databases and they are performed according to state of art. Efficiency improves overall execution on a degraded historical document with character detection. The normal relationship between the scale values and the current execution is difficult to find.

To recuperate the material with a couple of mistakes, create the nature of photos in the archives. The performance was excellent. The public dataset DIQA is used to evaluate this approach, and it contains occluded record photos at various levels. To reduce the obscurity in the OCR, an innovative technique based on neighborhood groups is used. The investigation [8][17] is done with the use of OCR on an open database. The recommended plan increased the OCR rate change to 11%. The Tesseract was used to evaluate the suggested model without a dialect display. The findings of the study suggest that combining the effects of obscurity and character attributes can be used to predict OCR precision.

Convolution Neural network produce the predominant success in the popularity of the character if the hand written photo in particular inside the curves and lines of the human written individual. A talented online Handwritten Person Popularity Machine for English Characters (OHR-E) using CNN (Convolution Neural Network) calculation is displayed in this provocative picture. However, the overall performance of this depends primarily on estimation and temporal complexity, and it also only takes into account the picture's bitmap format while neglecting other attributes. In addition to neural networks, genuine classifiers and support vector machines have developed solutions to this issue that offer accuracy in describing novel facts. The paper's form is broken down in the sections below. The third phase offers an overview of the several problems that have been raised thus far. The end of the suggested machine is provided in Section 4.

2. RELATED WORK

HDSR-Flor: A. F. De Sousa Neto, et al., Complex Scenarios, HDSR-Flor: A Robust End-to-End System for Handwritten Digit String Recognition in Real-World Situations. Deep Neural Networks are used to recognise handwritten letters [1] automatically. Gadariya, S. Chaturvedi, A. A. Khurshid [2] used a Spiking Neural Network (SNN) and a Leaky Integrate and Fire Model (LIF). By using a model SNN, it is possible to separate and identify a character object and a different type of handwritten character. Edge detection and extended histogram were used after pre-processing the input to separate the possible features of the image. The LIF structure improves computational efficiency. It is estimated that the neural properties are obtained by using a spiking neural network in this method at a computational efficiency of about 13 flops/1ms. A classifier called Support Vector Machine is used to compare the results of SNN. Post-processing operations are applied to identify objects and characters. Scan images are segmented to enable efficient recognition. In order to decide the final outcome of the LIF, we need some level network models of SNN that are combined

with the technologies of Support Vector Machines (SVM).

A new method for separating handwritten and machine-printed content from boisterous archives was introduced by ParulSahare and Sanjay B. Dhok.[3] For partitioning, relationship coefficients and probability-based minutes features are used. It has excellent isotropic and directional properties, so contourlet change is perfect for separating these large features. To recognize the machine-printed, hand-written, and commotional content, an arrangement of help vector machine classifiers is utilized. As the proposed calculation is general, it tends to be utilized for printed and handwritten writings in order of alternate contents. However, characterizing the current feature can be improved by including some nearby basic features, which can easily be combined with the current feature.

In the year 2018, Tavoli, R., and Mohammadreza Keyvanpour, M. [4] implemented swarm optimization to improve the weighted in the neural network. Based on particle swarm 11 optimization and multi-layer perceptron, Using two approaches, PSO and MLP, a new system for recognizing handwritten words from handwritten scripts is constructed. For English papers, this approach employs the IAM

English dataset. To detect the keyword, they created a different neural network for each word. It delivers a positivenumber if the test data matches the keyword. It has the highest accuracy when compared to the old methods.

A new ranking-based feature selection approach is proposed for handwritten character recognition [5] with different univariate measures are used to create component positioning, and an eager quest approach is proposed to pick the subset of elements ready to boost the results of grouping. An important non-parametric strategy that is used for characterizing behaving systems is K Nearest Neighbor (K-NN). A combination of positioning systems and insatiable inquiry procedures was utilized to choose highlight subsets with a broader array of highlights, which were added dynamically as they changed positions.

For reading the characters from the Indian document images, a bespoke model was created to segment the characters into multiple languages. On the basis of the auxiliary property of characters, essential division ways can be calculated. In addition, covered and joined characters are separated based on the chart separation hypothesis. Lastly, division results are verified with a support vector machine classifier that is particularly precise, and three novel geometrical shape-dependent characteristics are identified. The first and second components are based on the character's middle pixel, and the third component is based on the content's neighborhood data. We examine both an open and an exclusive database. When examining the CHARS74K numerals database, 99.84% precision was the highest when the proposed acknowledgment calculation was applied.

Sinusoidal parameters are used to construct a unique approach for online handwriting recognition [7]. The x- and y-facilities are also important because they are subordinates of the speed image (i.e. quickening). To test the validity of the feature, a character and word recognition task was done using hidden Markov models (HMM) and support vector machines (SVM). By fitting half cycles of a sine wave between the advancing low

intersection focuses, each of these factors (abundance, stage, and recurrence) is erased. The Assamese digit database, UNIPEN English character database, and UNIPEN ICROW-03 English word database were used to conduct the analysis. The findings show that abundance carries the most character-specific information, whereas stage contains the least.

We developed a robust approach for identifying damaged character pictures from ancient Kannada[8] poetry reports and handwritten character pixels aggregated from different uncontrolled contexts using convolutional neural networks. The Alex net has a 91.3 percent accuracy rate for printed characters and a 92 percent accuracy rate for handwritten characters. Printed datasets are extracted from the oldest papers, and writings from people aged 18-21, 22-25, and 26-30 can be gathered synthetically, with over-lapping still taken into account throughout the OCR post- processing phases. The semantic evaluation is conducted during the OCR after-processing stage.

Handwritten Number and English Character[9] Recognition System was introduced by using the technology of Back Propagation Neural network. A model can be trained with datasets through a backpropagation neural network. Test images are predicted using the trained model or trained dataset. The accuracy of the handwritten character is 44 percent, and the recognition rate for the numerical is 94 percent. This implementation 13 achieved a final recognition rate of 78%. The Feature Extraction of this method is not that efficient and the minimum number of test cases is required, so the recognition rate is low. Deep learning algorithms should be used to increase recognition rates.

In 2018, Seiya Iwata, Wataru Ohyama, and Tetushi Wakabayashi proposed a novel way to detect transition frames of Arabic captions for video retrieval [10]. detecting edges of still-in-progress news inscriptions. Identifying progress outline in news is also accomplished using an inter-outline content distinction when OCR is employed to perceive low- definition words. Contrasting this with this technique greatly enhances the exactness. The development of the sentence can be enhanced in the future by having subtitles that move. This system can be explored using different telecom projects.

An approach [11] for local incorrect rectifiers is proposed for rebuilding the nature of images in the archives with a few errors. This is so as to recoup the content with a few mistakes. This method's performance evaluation is based on the public dataset DIQA, which includes obscuring the record pictures at distinct levels. The OCR is being reduced through a novel approach based on neighborhood groups.

Sezer Karaoglu,[12] Ran Tao, Jan C. van Gemert, and Theo Gevers improved Con-Text: Text Detection for Fine-grained Object Classification by utilizing OCR techniques and a superior in class character 14 acknowledgment method. Unsupervised, generic, and efficient character recognition algorithms are used. To determine where the text is located, this technology detects the text background rather than the entire text region. These two technologies are used for text recognition. On ICDAR03, OCR machines and the best-in-class character recognition provide a 15% growth edge. Together, printed and visual text signals produce a fine-grain grouping and logo recovery.

Sezer Karaoglu, Ran Tao, and their colleagues [14] devised a method for eliminating words and logos from settings and photographs. The Fully unsupervised word box strategy is used here, which is a wholly unsupervised approach with a predetermined amount of recommendations. There are 2761 boxes in the content discovery dataset. Printed instructions at the word level are more strong than those at the character level, according to this study. Using large datasets, future research could improve the F-score. Ground truth and IOU thresholds overlap, and IOU thresholds increase as recall values decrease. A high retrieval score is more important than a high F score when it comes to phrase detection. For accessing the fine-grained location class and logo of a business, a textual hint is developed.

Block Wise Local Binary Count (BW-LBC) is a recently developed technique introduced by AbderrazakChahi, et al [15]. BW-LBC represents an industrial writer's writing 15 behaviour, which is developed from a set of associated characteristics and handwritten samples. All of the writing examples are filled as feature vectors using the 1NN (Nearest Neighbor) approach. The BW-LBC operator works by showing the thickness of white pixels within the various squares of the information double example. In comparison to previous systems, our methodology proved superior achievement on AHTID/MW and IFN/ENIT, as well as competitive activity on the alphabet CVL dataset. The effectiveness of this method will be improved by introducing the concept of support vector machine (SVM). This system achieves an average accuracy of 98.38 percent. This proposed solution uses the superior to deliver BW-LBC performance for the Arabic script.

In [16] 2017 a revolutionary method is proposed by Byeongyong Ahn, et al for detecting the text lines in degraded historical document images. As part of the proposed strategy, a traditional two-advance system has been proposed, in which binarization is first performed, then context lines are separated from the two-fold picture. To address the problems in recorded files, for example, report corruption, commotion in the structure, and slants. Slant and composing style are compensated for, and the fundamental content material square is separated. Experiments are accomplished on various databases and they're executed in line with the nation of art. the overall overall performance of degraded historic files with person detection is improved. Indicate whether the size values and the current execution have a normal connection. The schematic of the architecture in which initially, the enter is taken as photo or scanned copies of Hand written character. The pictures may additionally underneath is going many tactics of preprocessing; Segmentation and that they extract the function through using the optical individual reputation

3. PROPOSED METHOD

Pre-processing is a initial method for operations with snap shots at the bottom level of abstraction both enter and output are intensity images. The handwritten photographs are of the equal kind because the unique statistics captured by using the sensor, with an intensity picture typically represented through a matrix of picture function values (brightness). The purpose of pre-processing is an improvement of the picture facts that suppresses unwilling

distortions or complements some photograph features crucial for further processing, although geometric changes of photos (e.g. turn, scaling, and interpretation) are ordered amongst pre-getting ready strategies right here when you consider that comparative systems are utilized.

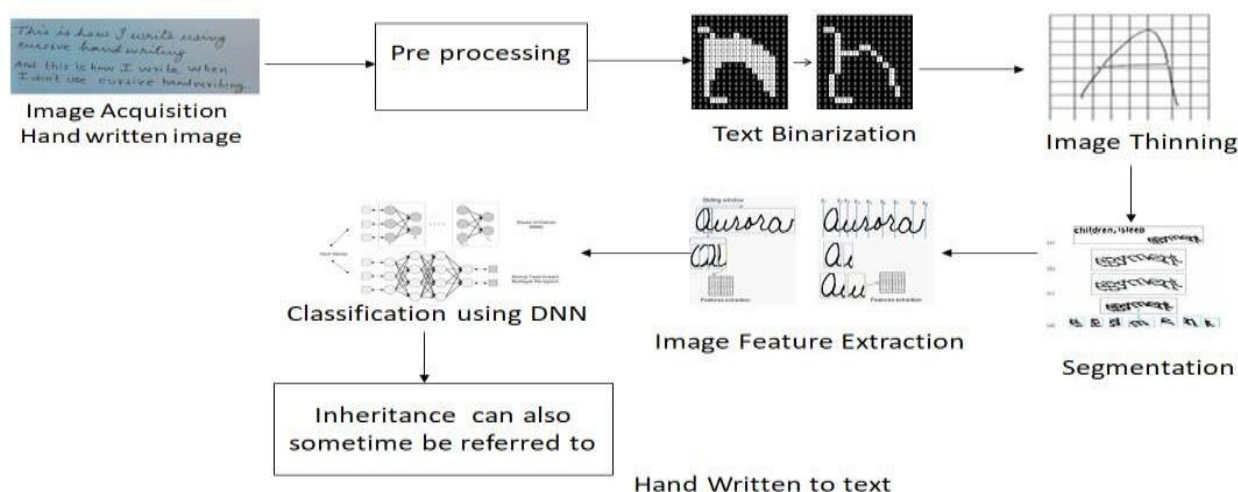
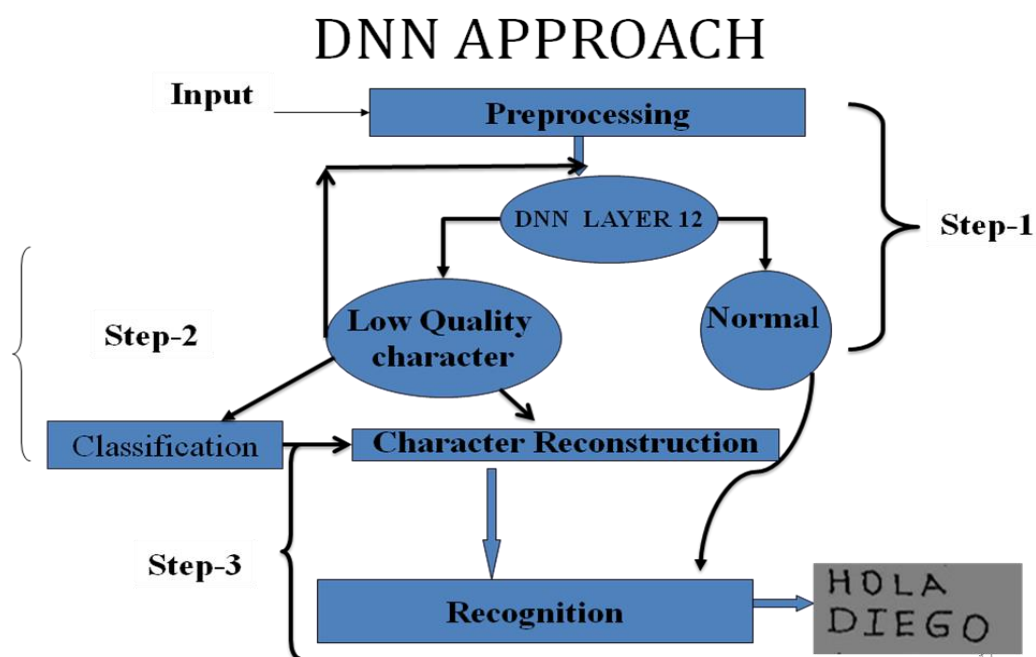


Figure 3.1 System Architecture

3.1 systems Architecture

Figure 3.1 depicts that the handwritten document is given as an input, in the preprocessing the step the noise is removed and text binarization is done, output of text binarization is converting text into 0's and 1's that is given as an input to the process image thinning, classification algorithm is used for classifying the character and features are extracted from the character that is given for recognition.



3.2 DNN CLASSIFICATION ALGORITHM

Figure 3.2 shows that flow of Classification using DNN in step 1 hand written document is given as an input and it is classified in to two Documents one is low quality and another is good quality document. If the character quality is very low, the step 1 will be repeated. In step 3 Good quality character document is sent for recognition and handwritten documents are converted into person understandable Text.

3.1.1 DNN Algorithm

1. Capture the image of the hand written character.
2. To enhance the quality of the picture using preprocessing method.
3. After the preprocessing, image thinning process will be taking place to remove selected foreground pixels from images. It consists of skeleton of hand written character.
4. Text binarization process is take for feature extraction of the image
5. Feature of the image is extracted to recognize the character which is already presented in image.
6. Finally, classification of the feature can be done by using Deep neural network (DNN).

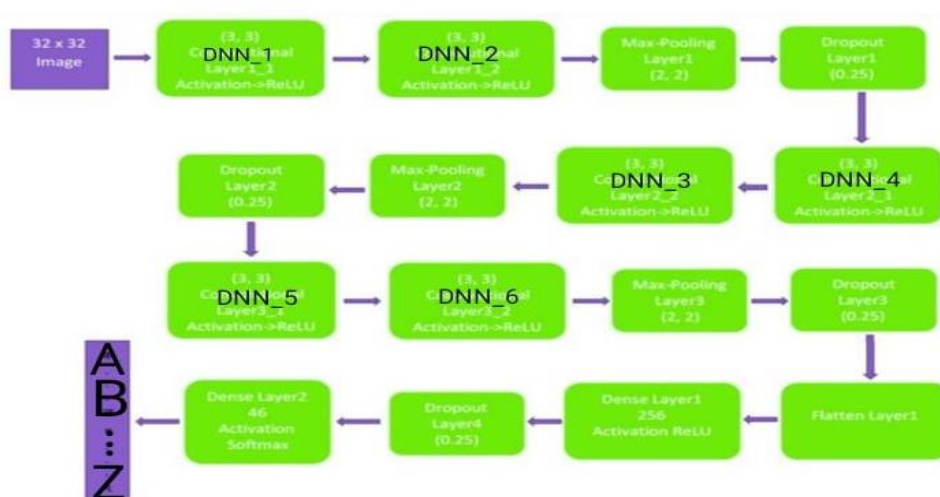


Fig: 3.2 Flow of Proposed Model

Figure 3.2 describes the flow of Proposed Model .There are 12 DNN layers are used for testing and training the output of the model is given below

3.2 IMAGE ACQUISITION

The Initial Stage of this proposed method is Image Acquisition. It is the Process under goes through Scanner, camera, mobile phones etc. Where, Hand Written Character can be obtained by using hardware. Image Acquisition is the process of creating a digital

representation of the visual characteristics in an image. The scanned images can be collected and stored in the data base for further process in future. The picture procurement procedure comprises of three stages; vitality reflected from the object of intrigue, an optical framework which centers the vitality lastly a sensor which measures the After the picture has been gotten, different strategies for preparing can be applied to the picture to play out the various vision undertakings required.

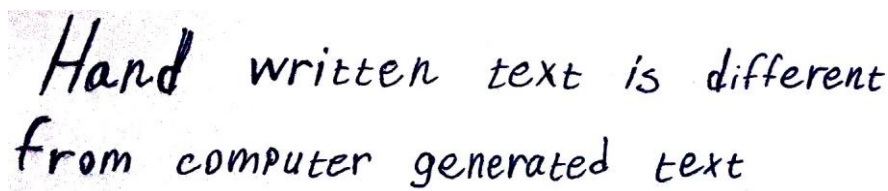


Fig. 3.4 Scanned Image

Figure 3.4 represent the hand written image that as it may, in the event that the picture has not been obtained acceptably, at that point the expected assignments may not be reachable, even with the guide of some type of picture improvement.

3.2 IMAGE ENHANCEMENT

Image enhancement is modifying digital images to produce the best outcomes for presentation. It is applied to enhance the image's quality. The image is improved using the PCA. A PC picture-preparation technique called Versatile Mean Adjustment is used to enhance differentiation in images. It changes the pixel allocation to more consistently increase out beyond the available pixel variety. A histogram shows the distribution of pixel intensity values when dealing out histograms. A poor image will have low pixel values, while a beautiful image will have high pixel values.

3.3 FILTERING

The fundamental step in many different types of computerised picture handling is to place an area around each pixel in an advanced image, investigate the estimates of the large number of pixels in that area according to some calculation, and then replace the first pixel's incentive with one based on the examination of the pixels. The local then repeats the process, moving gradually over each pixel in the image. In order to focus on the current pixel, the flexible deconvolution procedure first divides the pixels of a small window into three groups: lower force drive noise, unaltered pixels, and higher power motivation noise. If the inside pixel is present in the group of uncorrupted pixels, it will then be classified as either uncorrupted or defiled. Two boundaries that separate these three groups are necessary for that.

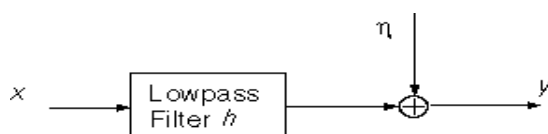


Fig. 3.5 Wiener Filter

In order to understand the flexible middle separating available, one must first understand what a middle channel is and what it performs (see Figure 3.5). The fundamental process in a wide variety of advanced picture processing is as follows: for each pixel in a computerised image, we place a region around it, divide the estimates of the large number of pixels in the region according to some calculation, and then replace the first pixel's incentive with one based on the analysis of the pixels in the region. The local then repeats the process, moving gradually over each pixel in the image.

3.4 SEGMENTATION

Segmentation is critical due to the fact the extract one may be reached in separation the diverse traces in the person without delay have an effect on the popularity rate. Segmentation can be achieved using remote line and curves in the cursive individual. It is the manner of slicing the man or woman right into a separate segment to get feature extraction of the individual.

It is a task that aims to separate a picture of a character arrangement into smaller pictures of individual images. A crucial need for determining the usefulness of conventional systems is character segmentation. According to the type of content and technique being pursued, several strategies can be categorised. Examples include the straight division strategy, acknowledgment-based division, and cut order strategy. A segmentation technique must have these properties to be widely useful. Capture perceptually significant clusters or areas, which frequently represent an image's overall characteristics. Two major challenges are being able to accurately define what is perceptually meaningful and being able to describe how a specific segmentation strategy works. To better comprehend the process and make it easier to compare various strategies, the attributes of a segmentation that results should have clear descriptions.

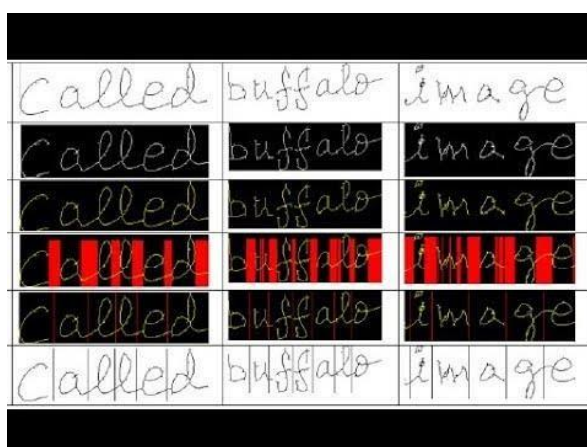


Fig. 3.6 Character Segmentation

As shown in Figure 3.6, segmentation algorithms should operate at speeds comparable to edges detection or other low-level visual processing approaches, which entails almost linear time and few constant factors. For instance, video processing applications can make advantage of a segmentation method that operates at multiple frames per second.

3.5 FEATURE EXTRACTION

It is well acknowledged that feature extraction is a more challenging problem of pattern recognition and aims to capture the important content of the character of the symbols. The actual raster image is the most straightforward approach to describe a character. Each character possesses a few traits that play a crucial role in example recognition. Characters have a variety of distinctive traits. In order to make the task of sorting the example straightforward, feature extraction shows the significant shape data that is included in an example. In this framework, feature extraction organises investigates these English character sections and selects an arrangement of a feature that can be used to separate those character sections in an intriguing way.

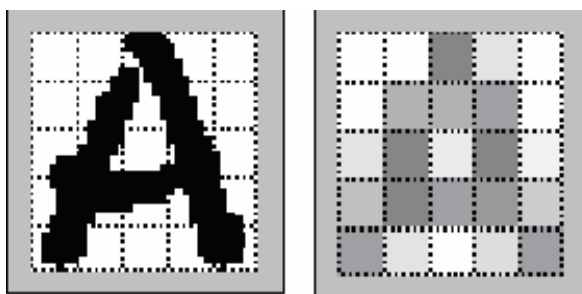


Fig. 3.7 Extracted Feature

Figure 3.7 is the image of feature extraction consists of smoothing techniques. It consists of the two processes first it undergoes cropping of an image and resizing of the image by using the matrix method. This stage is the heart of this framework because yields rely upon these features. Highlight extraction is the name given to a group of methods for estimating the significant shape data contained in an example so that the undertaking of grouping the example is made simple by a formal methodology. Among the unique configuration issues engaged with building a perceiving framework, maybe the hugest one is the choice of a set of features.

3.6 TEXT RECOGNITION

The aim of this process is automatic recognition of the patterns of the character. Initially, they identify the pattern of the character in different classes. In OCR is the structure of the character, numerals, and some special characters like a question, commas, etc., where the different characters are corresponding to the different classes of the handwritten character. They built a prototype for the character recognition of the human handwritten character methods are consisting of the recognition of unknown character are compared to the already contained character in the database, description and assigned the class the given matches. In most of the techniques consist of character recognition, the training process has been performed in advance. Some systems do however recognition of the character using the already presented database.



Fig. 3.8 Matching of Text with Feature Class

The result of the suggested system is shown in Figure 3.8. The character template is extracted using this technique. Direct matches with a set of prototype characters that represent each potential member of the class are used in place of the matrix that holds the picture of the input character. Each prototype's distance from the pattern is calculated, and the class of prototype that provides the best matches for the pattern is given. These techniques calculate and extract a character's signification measurement, which is then compared to a description of the character classes learned during training phases. Recognition is given by the most accurate description. The sign and the character are represented by the feature, which is given as a numerical value in the feature vector.

3.7 TYPES OF FILTERS

In image pre-processing, various types of filters are used to reduce the noise from the image. The common filters are median filter, Weiner filter, Gaussian filter, mean filter and Gabor filter which are used to reduce different types of noises such as Salt and Pepper noise, Additive noise, Gaussian noise and Speckle noise. There are two types of filtering technique such as Linear and Non-linear filtering where in Linear filtering edges are not persevered properly and speed of removing noise is high and in Non-Linear filtering edges is preserved much better than linear filtering.

3.8 MEDIAN FILTER

This filter is mainly used to eliminate the impulse noise in medical image. To reduce the noise and to preserve edges median filter is more effective than convolution and median filter is a Non-Linear filtering model. Median filter applies the window on the pixel with need to represent and check the value of the nearby pixels of the image.

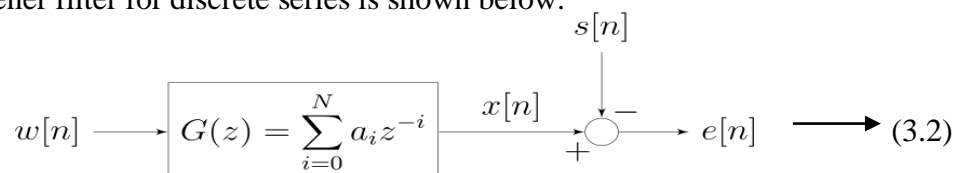
The equation of median filter is:

$$I'(u, v) \leftarrow \text{median} \{I(u+i, v+j) \mid (i, j) \in R\}. \quad (3.1) \longrightarrow$$

The pattern of neighbours in median filter is called as 'window' and the pixel are sorted in numerical order from window and then replace than pixel with median pixel. It is a type of smoothening technique where in smoothening process it removes noise effety in smooth patches but it should also preserve the edges which is important for the visual aspect of an image.

3.8.1 WEINER FILTER

The main principle of Wiener filter is to remove additive noise and invert blurred image. The Wiener filter is a linear filtering technique which is best in minimizing the mean square error. In the implementation of Wiener filter, we have to generalize the inverse filter when the inverse filter is singular. There are three possible cases of solution for Wiener filter. A block diagram of FIR Wiener filter for discrete series is shown below:



In this method, the power spectra have to be estimated for original image and additive noise where the white additive noise has equal power spectra and variance of noise. They are Non-causal filter where both past and future data is required, Causal filter which uses only past data is used and the finite impulse response case where only input data is used.

3.8.2 GAUSSIAN FILTER

The Gaussian filter is a linear filtering model which has minimum group delay and consider as a time domain filter. The Gaussian function for $x \in (\alpha, -\alpha)$ and requires infinite window length. It delays rapidly so it used to truncate the filter window and truncation introduces errors. The general equation of Gaussian filter is:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/(2\sigma^2)} \quad (3.3) \quad \longrightarrow$$

The impulse responses of Gaussian filter in electronics and signal processing is Gaussian function. To avoid these types of errors and to achieve better result different window function is used.

3.8.3 MEAN FILTER

The mean filter is an easy and straightforward method to implement which smoothers the image where it decreases the intensity difference between one pixel to another. The mean filter will replace the centre pixel value of window with the mean of all the pixels in the image. (5.4)

$$\text{Mean filter} = \frac{\sum (\text{All the pixels in the window})}{\text{Number of pixels in the window}}$$

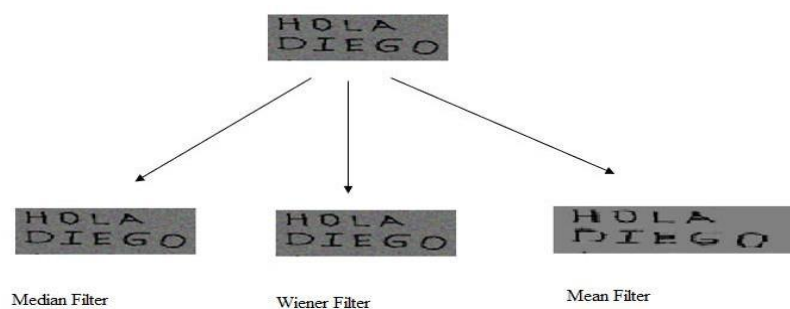


Fig. 3.12 Comparison of filters for salt and pepper noise

The figure 3.12 shows the output image obtained from various filter after removing the salt and pepper noise.

3.9 FEATURE EXTRACTION TECHNIQUES

3.9.1 CROPPING OF IMAGE

This algorithm is employed for cropping the border of the image to pick out the specified character and that they standardize the sub pictures. The image standardization is finished by finding the most rows and column with 1s and with peak purpose, increase and reduce the counter till meeting the white area or the road with all 0s.

3.9.2 RESIZING AN IMAGE

The image resizing is the process that follows the pre-processing techniques. It reduces the size of the image from Hand written document. Image can be resizing again to meet the requirement for the matrices and values of 1 will be assign to all pixel where all 10 by 10 box are filled with 1s. At end of the resizing process 5 by 7 matrices is concatenated into a stream.

3.9.3 TEXT RECOGNITION

In most of the techniques consist of character recognition, the training process hasbeen performed in advance. Some systems do however recognition of the character using the already presented database. In OCR is the structure of the character, numerals, and some special characters like a question, commas, etc., where the different characters are corresponding to the different classes of the handwritten character.

4. RESULTS AND DISCUSSION

4.1 ACCURACY

Accuracy shows the description of the systematic mistakes, degree of the statistical bias; as the purpose a distinction among a end result and a real cost, ISO calls this trueness. It defines accuracy as describing aggregate of the both form of the observational errors above, so final high accuracy requires both high precision and excessive trueness.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \longrightarrow (4.1)$$

TP=True Positive; FP=False Positive; TN=True Negative; FN=False Negative

4.2 SENSITIVITY

Sensitivity is also called as true positive rate, the recall, or probability of the detection. In some field measure the proportion of the actual positive that are correctly identified.

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN}) \longrightarrow (4.2)$$

TP=True Position, FN=False Negative

4.3 SYSTEM SPECIFICITY

The specificity tells us how likely the test is to come back negative in someone who does not have the characteristic.

$$\text{Specificity} = \text{TN} / (\text{FP} + \text{TN}) \longrightarrow (4.3)$$

TP=True Positive, FP=False Positive, TN=True Negative

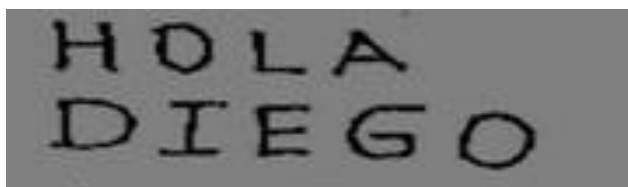


Table: 1 Training Dataset

Methods used	No.of Classes	Accuracy
MLP	10	86
20 LAYER CNN	104	89
SVM CLASSIFIER	51	91
CNN	46	93
12 LAYER CNN	46	98.91
12 LAYER DNN	50	99.5

Model .summary ()

Layer (type)	Output shape	Param#
DNN_1(DNN_2D)	(None,28,28,32)	420
DNN_2(DNN_2D)	(None,30,30,32)	1268
Dropout_1(Dropout)	(None,14,14,32)	5
DNN_3(DNN_2D)	(None,16,16,32)	5

DNN_4(DNN_2D)	(None,18,18,32)	26786
Dropout_2(Dropout)	(None,18,18,32)	36789
Flattern_1(Flattern)	(None,1600)	0
DNN_1(DNN_2D)	(None,28,28,32)	0
DNN_2(DNN_2D)	(None,30,30,32)	509876
Droput_3(Dropout)	(None,16,16,32)	0
Dense_1(Dense)	(None,256)	20867

Total Params: 500,760

Trainable Parameters:500,760

Non-Trainable param:0

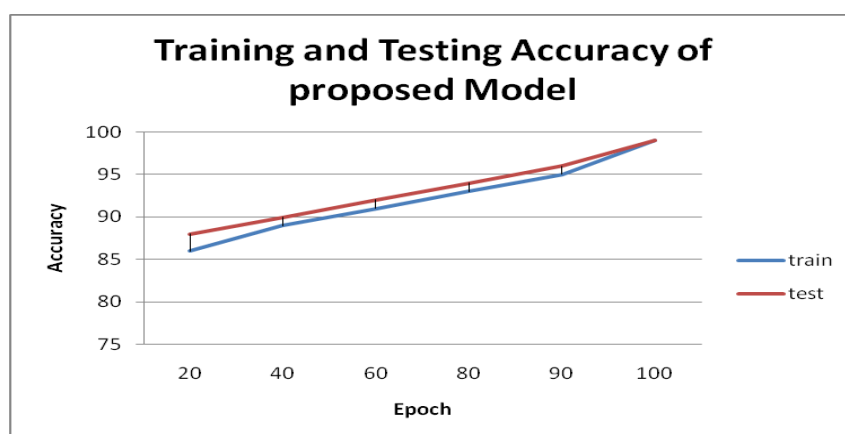


Fig 4.2.Proposed DNN Model Accuracy

Fig 4.2 describes the Accuracy of training data set and testing dataset of Proposed model , 500 parameters are taken into consideration and testing training have been done , comparison between the training and test is given in the figure

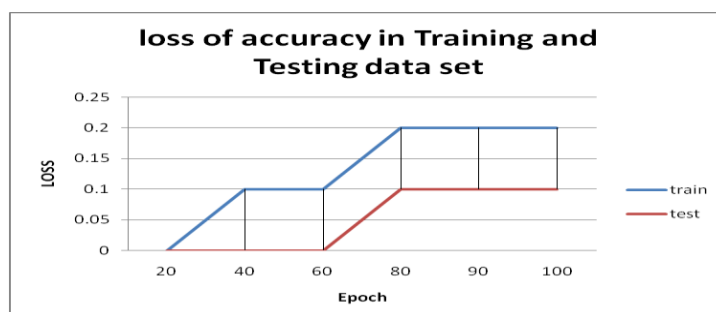


Fig 4.3.Proposed DNN Model Loss

Fig 4.3 describes the Loss of training data set and testing dataset of DNN Proposed model , 500 parameters are taken into consideration and testing training have been done , comparison between the training and test is given in the figure .Showing the procedure of our endeavor dataset of a transcribed individual has been taken from record or people who have composed the man or lady in the paper. A dataset has comprised of the top case letter and also the lowercase individual and moreover; it comprises of an amount datasets. The limit of the

individual is exceptionally too hard to even think about understanding and extreme to recognize the person, where the stroke edges of the person including various shapes. Datasets is gathered and saved in the information base for include extraction of the person. The experiment is prepared with various innovations of a neural organization yet doesn't show that much compelling way acknowledgment of the transcribed person contrasting and profound neural organization. The acknowledgment of the person utilizing this innovation shows the most trusted and successful way in the acknowledgment of the person in the written by hand character. At first, the record goes through in the different course of preprocessing and the picturething binarization of the pictures is occurring after that division the picture will happen. At last, the element is separated by utilizing the DNN and contrasts the elements and the OCR.

Table 2. Comparison of filters Noise

Types of filters Noise(%)	Salt and pepper	Gaussian	Speckle
2d median filter	98.32	74.89	80.6
Mean filter	88.01	89.78	98.48
Wiener filter	91.56	64	96.78

Table 2 show the noise level character and capacities limit the depiction and make the affirmation methodology high innovation. In OCR, a calculation might be instructed basically founded on a measurement set of perceived handwritten text so you can figure out how to group the characters that include in the check set precisely.

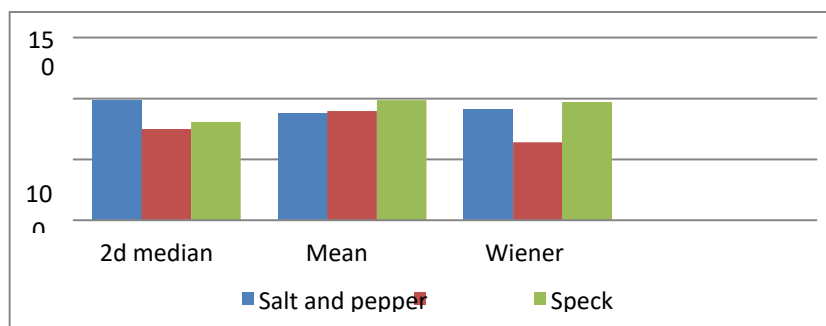


Fig 4.6 Comparison of filters

Graph.1 shows the correlation of the channels in the rate. 2D middle channels are more successful in the investigation of the various channels. Looking at the other two channels, 2D middle channel shows the high effectiveness in the decrease of undesirable commotion in the

pictures. In this examination, preprocessing goes through with the 2D middle channel on the grounds that the PSNR esteem another channel low contrasting with the other channel where division of this interaction utilized the versatile mean shift calculation.

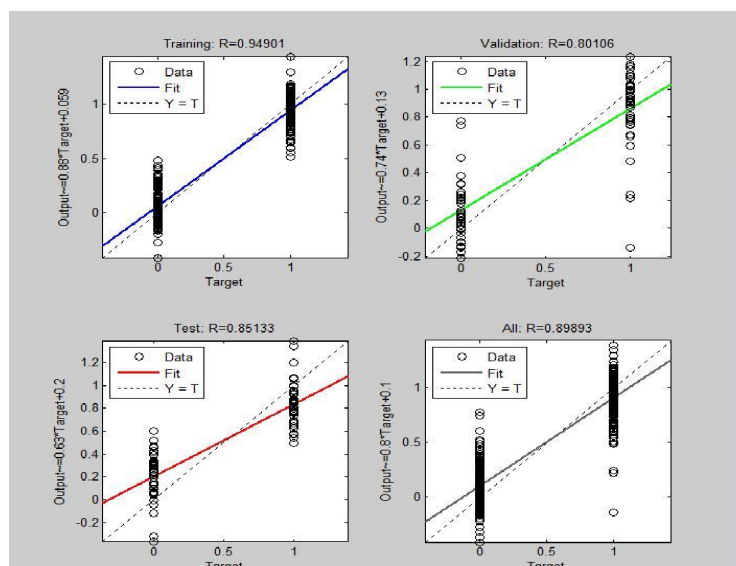


Figure 4.7 Classification Result

Figure 4.7 shows the training data output and validation output. Training set approximately matched with the target output. The blue line and dashed line highlight the training set image with target value. The red line and dashed line show the test image with target value. Accuracy of the training set and test data is .85 and .89 respectively. From figure we came to conclude that the proposed system gives better accuracy rate during the raining and testing.

Table 3: Comparison between Existing Method and Proposed Method

METHOD	ACCURACY
Existing Method (CNN12 LAYER)	98.91
Proposed Method (DNN 12 LAYER)	99.5

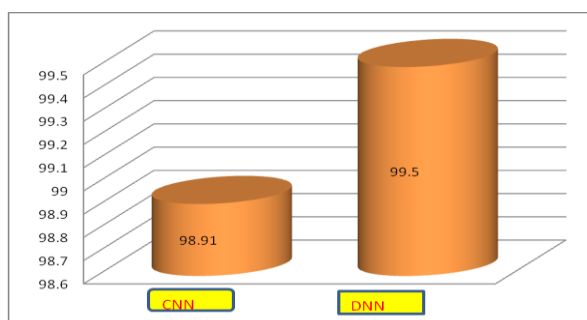


Fig 4.7 comparison between CNN and DNN

Figure 4.7 shows the comparison between the existing method CNN with 12 layers and proposed Method DNN with 12 layers. We achieved accuracy 99.5 because of filters. Wiener filter reducing the noise from the character and features are extracted from the character image .our proposed system gave good accuracy and less loss.

5. CONCLUSION

However, the Deep Neural Network plays a more effective role in the identifying the character of the human written Hand writing and accuracy is reached to 99.5%. By showing in numerous enhance in the extractions of the shapes of the character comparing to exiting method. This survey shows that extraction of the character is difficult task and least technology provides a high recognition rated method used to find the text written by human are more complexity and inefficient. This Technology increases the time complexity and the accuracy of the hand written character. An assortment of strategies has risen, impacted by improvements in related fields, for example, picture acknowledgment. In this paper, we present the handwritten character recognition algorithm used online. These methods use various classifiers to deliver improved accuracy. Information on several classifiers used in character recognition algorithms is provided in this article. In the future, this might be combined with other emerging technologies to increase the adoption rate, which would be advantageous for both the public and private sectors.

6. REFERENCES

1. Kieu, V. C., Cloppet, F., & Vincent, N. (2016). “*Local blur correction for document images*”. 2016 23rd International Conference on Pattern Recognition (ICPR). doi:10.1109/icpr.2016.7900269.
2. Karaoglu, S., Tao, R., van Gemert, J. C., & Gevers, T. (2017). “*Con-Text: Text Detection for Fine-Grained Object Classification*”. IEEE Transactions on Image Processing, 26(8), 3965– 3980.doi:10.1109/tip.2017.2707805.
3. Vo, Q. N., Kim, S. H., Yang, H. J., & Lee, G. S. (2018).” *Text line segmentation using a fully convolutional network in handwritten document images* “. IET Image Processing, 12(3), 438– 446. doi:10.1049/iet-ipr.2017.0083.
4. Karaoglu, S., Tao, R., Gevers, T., & Smeulders, A. W. M. (2017).” *Words Matter: Scene Textfor Image Classification and Retrieval*”. IEEE Transactions on Multimedia, 19(5), 1063–1076. doi:10.1109/tmm.2016.2638622.
5. Chahi, A., El Khadiri, I., El Merabet, Y., Ruichek, Y., & Touahni, R. (2018).” *Effective feature descriptor-based new framework for off-line text-independent writer identification*”. 2018 International Conference on Intelligent Systems and Computer Vision (ISCV).doi:10.1109/isacv.2018.8354072.
6. Ahn, B., Ryu, J., Koo, H. I., & Cho, N. I. (2017). “*Textline detection in degraded historical document images*”. EURASIP Journal on Image and Video Processing, 2017(1).doi:10.1186/s13640-017-0229-7.
7. Monisha G.S., Malathi S. (2021).” Effective Survey on Handwriting Character Recognition”. In: Singh V., Asari V.K., Kumar S., Patel R.B. (eds) Computational Methods and Data Engineering. Advances in Intelligent Systems and Computing, vol

1257. Springer, Singapore. https://doi.org/10.1007/978-981-15-7907-3_9.
8. Zhili Zhou, Huiyu Sun, Rohan Harit, Xianyi Chen, And Xingming Sun,” Coverless Image Steganography Without Embedding” Icccs 2015, Lncs 9483,Pp. 123–132, Doi: 10.1007/978-3-319-27051-7_11, 2015.
9. Sharma, A. (2022). Some Invariance Results for Isometries. International Journal on Recent Trends in Life Science and Mathematics, 9(2), 10–20. <https://doi.org/10.17762/ijlsm.v9i2.131>
10. Weihui Dai, Yue Yu, Bin Deng,” Bintext Steganography Based on Markov State Transferring Probability”, Icis 2009, November 24-26, 2009 Seoul, Korea Copyright © 2009 Acm 978-1-60558-710-3/09/11.
11. Z. Yang, Y.-J. Zhang, S. Ur Rehman, And Y. Huang, “Image Captioning with Object Detection and Localization,” In International Conference on Image and Graphics. Springer, 2017, Pp. 109–118.
12. Wikipedia. (2020). Steganography. [Online]. Available: [Https://En.Wikipedia.Org/Wiki/Steganography](https://En.Wikipedia.Org/Wiki/Steganography).
13. [22]N. F. Hordri, S. S. Yuhani, And S. M. Shamsuddin, “Deep Learning and Its Applications: A Review,” In Proc. Conf. Postgraduate Annu. Res. Informat. Seminar, 2016, Pp. 1–6.
14. [23]P. Wu, Y. Yang, And X. Li, “Image-Into-Image Steganography Using Deep Convolutional Network,” In Proc. Pacific Rim Conf. Multimedia. Cham, Switzerland: Springer, 2018, Pp. 792–802.
15. P. Modiya and S. Vahora, “Brain Tumor Detection Using Transfer Learning with Dimensionality Reduction Method”, Int J Intell Syst Appl Eng, vol. 10, no. 2, pp. 201–206, May 2022.
16. [24]P. Wu, Y. Yang, And X. Li, “Stegnet: Mega Image Steganography Capacity with Deep Convolutional Network,” Future Internet, Vol. 10, No. 6, P. 54, Jun. 2018.
17. [25] X. Duan, K. Jia, B. Li, D. Guo, E. Zhang, And C. Qin, “Reversible Image Steganography Scheme Based on A U-Net Structure,” Ieee Access, Vol. 7, Pp. 9314–9323, 2019.
18. T. P. Van, T. H. Dinh, And T. M. Thanh, “Simultaneous Convolutional Neural Network for Highly Efficient Image Steganography,” In Proc. 19th Int. Symp. Commun. Inf. Technol. (Iscit), Sep. 2019, Pp. 410–415.
19. R. Rahim And S. Nadeem, “End-To-End Trained Cnn Encoder-Decoder Networks for Image Steganography,” In Proc. Eur. Conf. Comput. Vis.(Eccv), 2018, Pp. 1–6.
20. Z. Wang, N. Gao, X. Wang, J. Xiang, And G. Liu, “Stent: A Style Transformation Network for Deep Image Steganography,” In Proc. Int. Conf. Neural Inf. Process. Cham, Switzerland: Springer, 2019, Pp. 3–14.
21. Ghazaly, N. M. . (2022). Data Catalogue Approaches, Implementation and Adoption: A Study of Purpose of Data Catalogue. International Journal on Future Revolution in Computer Science & Communication Engineering, 8(1), 01–04. <https://doi.org/10.17762/ijfrcsce.v8i1.2063>
22. K. Yang, K. Chen, W. Zhang, And N. Yu, “Provably Secure Generative Steganography Based on Autoregressive Model,” In Proc. Int. Workshop Digit. Watermarking. Cham, Switzerland: Springer, 2018, Pp. 55–68.

23. S. Baluja, "Hiding Images in Plain Sight: Deep Steganography," In Proc. Adv. Neural Inf. Process. Syst., 2017, Pp. 2069–2079.
24. Philip, A. M., and D. S. . Hemalatha. "Identifying Arrhythmias Based on ECG Classification Using Enhanced-PCA and Enhanced-SVM Methods". International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 5, May 2022, pp. 01-12, doi:10.17762/ijritcc.v10i5.5542.
25. R. Zhang, S. Dong, And J. Liu, "Invisible Steganography Via Generative Adversarial Networks," Multimedia Tools Appl., Vol. 78, No. 7, Pp. 8559– 8575, Apr. 2019.
26. S. Islam, A. Nigam, A. Mishra, And S. Kumar, "Vstegnet: Video Steganography Network Using Spatio-Temporal Features and Microbottleneck," In Proc. Bmvc, Sep. 2019, P. 274.
27. [33]T. Fang, M. Jaggi, And K. Argyraki, "Generating Steganographic Text With Lstms," Arxiv Preprint Arxiv:1705.10742, 2017.
28. Z. Yang, Y.-J. Zhang, S. Ur Rehman, And Y. Huang, "Image Captioning with Object Detection and Localization," In International Conference on Image and Graphics. Springer, 2017, Pp. 109–118.
29. D. Bahdanau, K. Cho, And Y. Bengio, "Neural Machine Translation by Jointly Learning to Align and Translate," Computer Science, 2014.
30. L. Shang, Z. Lu, And H. Li, "Neural Responding Machine for Short-Text Conversation," Pp. 52–58, 2015.
31. T. Mikolov, M. Karafit, L. Burget, J. Cernock, And S. Khudanpur, "Recurrent Neural Network Based Language Model," In Interspeech 2010, Conference of The International Speech Communication Association, Makuhari, Chiba, Japan, September, 2010, Pp. 1045–1048.
32. Vanitha, D. D. . (2022). Comparative Analysis of Power switches MOFET and IGBT Used in Power Applications. International Journal on Recent Technologies in Mechanical and Electrical Engineering, 9(5), 01–09. <https://doi.org/10.17762/ijrmee.v9i5.368>
33. Lingyun Xiang , Shuanghui Yang , Yuhang Liu , Qian Li And Chengzhang Zhu Feng Liu, Xuan Zhou, Xuehu Yan, Yuliang Lu And Shudong Wang, "ImageSteganalysis Via Diverse Filters and Squeeze-And-Excitation Convolutional Neural Network", Mathematics 2021, 9, 189. <https://doi.org/10.3390/Math9020189> ,2021.
34. Zhongliang Yang, Xiaoqing Guo, Ziming Chen, Yongfeng Huang, And Yu- Jin Zhang, "Rnn-Stega: Linguistic Steganography Based on Recurrent Neural Networks", Ieee Transactions on Information Forensics and Security, Doi: 10.1109/Tifs.2018.2871746, September 2018.