

RECOGNITION OF ONLINE HANDWRITTEN TELUGU LETTERS FOR DIFFERENT DOMAINS AND ORGANIZATIONS

P.V. RAMANA MURTHY¹, CH. G.V.N. PRASAD²

¹Research Scholar, Rayalaseema University, Kurnool, AP, Associate Professor, Department of CSE, Malla Reddy Engineering College (Autonomous), Hyderabad, (Telangana), INDIA (Email id: ramanamurthy19@gmail.com)

²Professor, Department of CSE, Sri Indu College of Engineering & Technology (Autonomous), Hyderabad, (Telangana), INDIA (Email id: prasadch204@gmail.com)

(Corresponding author: P.V. Ramana Murthy Email id: ramanamurthy19@gmail.com)

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ABSTRACT

Machine learning and neural networks are trending technologies used in different kinds of handwritten (HW) pattern recognition of various research areas. Therefore it is very hard to distinguish and recognise the hand written characters of different persons. Recognition of characters related to telugu language is a part of pattern reorganisation that happen to the idea of research during the past some years. Neural networks (NN) are playing a significant role in telugu HW character recognition. HW detection is the capability of a digital computer to receive and understand intelligible HW input from documents, images, touch screens and other electronic devices etc. These all may be online or offline, in this context online recognition includes conversion of pen tip digital movements into a list of originates used as input for the categorization system where as offline recognition uses images of characters like input. For HW reorganization NN has been achieved and improve the efficiency up to 98.3% this is good achievement.

Keywords: Machine learning, neural networks, telugu, handwritten characters, vatu, gunintham, pattern reorganization

Abbreviations: TL, Telugu letters; VTU, Vothulu; NN, Neural networks; HW, handwritten; MLPS, multilayer perceptrons; HWR, handwritten character recognition; CNN, Convolution neural network.

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I. INTRODUCTION

This exploration goes for a programmed comprehension of on line record Telugu letters (TL) and Vothulu (VTU) composed on a digital tablet or any display screen, without digital model (paper and pen). The proposed model includes two substantial degrees: Telugu vothulu and hallulu acknowledgment and secondary similarity examination. A combination of distinct classifiers has been applied to accomplish excessive precision for the acknowledgment of snapshots. A few on the online and offline highlights are utilized inside the primary examination stage to recognize the spatial connections among snap shots. A setting interchanges the letter shape that has been meant to exchange over the records into their TEX strings which can be thusly changed over into letter role. Relevant statistics have been utilized to address a few structure elucidation errors. Another approach for assessing the display of the proposed framework has been defined. Trials on a dataset of widespread length

unambiguously boost the achievability of the proposed framework. even though an outstanding deal of work has been accounted for acknowledgment in English and Asian languages, for example, Japanese, Chinese, and so on., and not very many endeavors on Indian dialects like Hindi, Tamil, Telugu, Kannada and so on. In this work handwritten character recognition (HWR) model for telugu [South Indian language] has been developed with high accuracy, less training time and time of classification, As a part of the previous work applies on low attainment knowledge of the established HWR to each letter and offline datasets. Instances of HWR contain pixel densities over set of a picture, in this section ebb and drift, measurements, and numerous flat and vertical strains has to be calculate f. C. Vikramet. AI utilized multilayer perceptrons [MLPS] and got a precision of 83.5% on HW Telugu individual datasets.

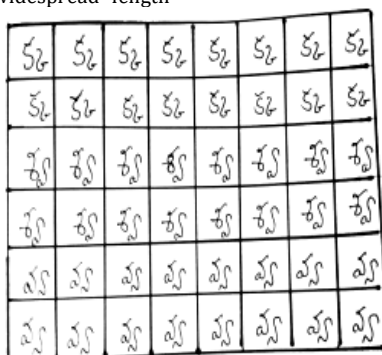


Figure: 1 example data set

Fig.1. shows that data set from Telugu letters i.e.kaagunithalu and shay votthuluetc, these all are selecting from data set which are available at MIT hub data set. Around 300 samples are placed as image models at final training samples are analysed.

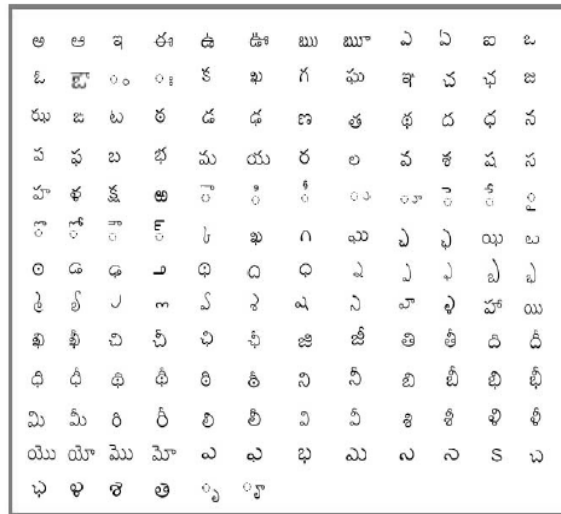


Figure: 2. 150 data from available data sets

Fig.2 explains about data set example from Unicode values each letter contains single Unicode values based on this pre-processing is to be performed.

Class Id	Telugu Symbol	Unicode
0	అ	0C05
1	ఆ	0C06
2	ఇ	0C07
3	ఈ	0C08
4	ఉ	0C09
5	ఊ	0C0A
6	ఋ	0C0B
7	ౠ	0C60
8	ఎ	0C0E
9	ఋ	0C0F
10	ఐ	0C10

Figure: 3.Unicode values

Fig. 3 is the symbols related to telugu characters and unicodes these all have been used to trained the MI techniques.

II. LITERATURE SURVEY

[1] P. N. Sastry, T. R. V. Lakshmi, N. V. K. Rao, T. V. Rajinikanth and A. Wahab 2014 Zonal based totally element extraction is utilized in the present proposed method. The individual image is isolated right into a predefined wide variety of zones and an authentic detail is figured from every this sort of zones.

Ordinarily, this element depends on the pixels contained in that sector. The dark estimations of the pixels in that chose zone are summarized to frame detail for that area in that photo. The highlights of the huge variety of zones inside the photo shape and element vector that is utilized for writing with the aid of

hand individual acknowledgment. Utilizing this Zoning method the acknowledgment precision is visible as 78%.

[2] S. D. Prasad and Y. Kanduri 2016 In any case, none of them deliver 100% precision in the acknowledgment of Telugu characters. Along these strains, it's far territory of progressing studies. Our exertion is predicted to improve the precision in Telugu man or woman acknowledgment. This propelled us to attempt this work. Zonal based detail extraction is applied within the gift proposed paintings. We exhibited two techniques for this reason. The number one strategy relies upon on the Genetic Algorithm and utilizations of versatile zoning topology with

separated geometric highlights. In the following method, zoning is completed in a static manner and utilizations separation, thickness primarily based highlights. In the two settings, we utilize the K-Nearest Neighbours (KNN) calculation for order purposes. The person picture is partitioned into a predefined wide variety of zones and highlights of the giant range of zones within the photo shape an element vector this is utilized within the grouping duration of transcribed character acknowledgment. Utilizing the primary approach we acquired correctness's of 100 percent and 82.Four percent for 11 and 50 photographs in my view. Utilizing the second method we were given exactness's of a hundred percent and 88.Eight percent for eleven and 50 images for my part.

III. PROBLEM STATEMENT

HWR has been one of the dynamic and testing studies zones inside the discipline of image getting ready and design recognition. Since 1929, some of the individual acknowledgment frameworks have been proposed and are utilized for even industrial enterprise reasons. A few applications including, organization related to checks, postal orders, examination related information's are help for offline frameworks. Working in Postal assist need us to interpret and bring something like 30 million manually written envelopes each and every day. The difficulties are to do mail-arranging that assure each one of these a huge quantity of letters arrive at their desires. HWR difficulty shifts amongst varied languages and letters because of unique shapes, strokes, and a variety of characters. Telugu, a South Indian language that positions 1/3 by using the variety of local speakers in India. Fifteenth in the Ethnologue rundown of maximum- communicated language in international and is the maximum typically communicated in Dravidian language on earth. Around 800 million people use Telugu as they speak to people and write explanations. Telugu content has 18 vowels and 36 consonants, of which 13 vowels and 35 consonants are in like way use. all of the Indic contents, the Telugu content has the largest range of vowels and consonants. Also, Telugu incorporates numerous similar formed characters; every now and then a character varies from its comparative one with a complete zero (anusvāra), half of-zero (arthanusvāra or candrabindu) and visarga to bypass on extraordinary shades of nasal sounds. That improves hard to accomplish execution with the dependable method simply because it prevents to work with Telugu manually written and gives some acknowledgments. Manually written person acknowledgment can be on the online or offline. In this specific situation, on line HW includes a change of computerized pen-tip traits right into a rundown of instructions, applied as a contribution for the order framework

at the same time as offline recognition uses photographs of characters as data. A part of the earlier works applies superficial getting to know with hand-structured characters on each the offline & online datasets. Instances of HWR include pixel densities over districts of the picture, individual ebb and drift, measurements, and some of the flat and vertical traces.

IV. EXISTED METHODS

This algorithm used only single characters of Telugu language. But there are many characters with 'vattu' and 'gunintham' which were shown in the below figure. As there are very less contributions on Telugu language characters, I couldn't find the dataset consisting of all these characters. But the characters used in this project are like vowels and consonants in English. Due to time constraints I didn't generated dataset with all those characters. In future, I want to extend this algorithm from character recognition to text recognition by creating my own dataset.

V. METHODOLOGY

A.Requirements

The evaluation metric for the model will be transcription accuracy on the test images in the HP dataset of Telugu characters. Accuracy will be defined as correctly predicting handwritten Telugu character in the image. The model must correctly predict not only the number of digits present but also correctly identify each of those digits. As noted above regarding benchmarking against previous work results, I will evaluate it against some other models like handwritten Hindi/ Tamil/ Bengali character recognition in both accuracy and speed.

B. Data Investigation

The dataset is downloaded from the HP Labs India site or MIT data set [1]. This dataset consists of approx. 270 examples of each one of 138 Telugu "characters" composed via nearby Telugu authors. The dataset includes a huge collection of unmistakable characters in view of numerous human beings corporations' composition styles. The characters are made on hand for download as TIFF files. An element of these individual pics are mind-boggling molded and firmly related to others. Telugu content material has 18 vowels and 36 consonants of which thirteen vowels and 35 consonants are in like manner use. Telugu content is for the maximum element non-cursive in fashion and sooner or later, pen-up extra often than no longer isolates the important graphemes but no longer usually. In this way, the important graphemes of the content, for example, loose vowels, consonants, vowel diacritics, and consonant modifiers are incorporated into the photograph set shown in fig.4. Likewise covered are some consonant-vowel units which can't be successfully portioned. Likewise, the photograph set additionally includes some pixels which do not have a semantic translation but have solid example crosswise over essayists and help reduce the whole variety of images to be amassed. In this manner, sincerely there are 138 photos. These are altogether allowed to Unicode characters. The characters are made available for download as TIFF records. The first inconsistent envisioned square pictures are resized into eighty x 80 square snapshots and spared them as JPG files.



Figure: 4.Telugu letters vowels

C. Convolution neural network algorithm

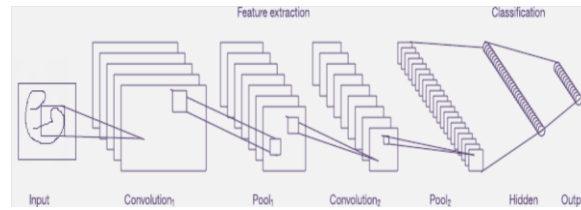


Figure: 5.CNN network

Fig.5. Clarifies the pooling convolution version, utilizing this model each letter has been organized with an auxiliary version. A trendy design of CNN that incorporates two essential components: consists of extraction and order. In the factor extraction layers, every layer of the machine gets the yield from its spark off a past layer as its data and passes the prevailing yield as a contribution to the subsequent layer. CNN engineering is produced from the combination of 3 styles of layers:

convolution

max-pooling

Characterization.

The convolutional layer and max-pooling layer are forms of layers inside the low and center diploma of the system. The even-numbered layers work for convolution and bizarre-numbered layers picture for the maximum pooling activity. The given hubs of the convolution and max-pooling layers are assembled right into a 2D aircraft that is referred to as spotlight mapping. Each aircraft of the layer normally decided with the mix of at least one plane of the past layers. The hub of the plane is associated with a touch district of each related plane of the past layer. Every hub of the convolution layer concentrates highlights from the records snapshots through convolution activity on the records hubs. The most pooling layer changed works include regular or engendering interest at the information hubs. The more elevated level highlights are gotten from the produce characters of the decrease-degree layers. As the highlights spread to the maximum notable layer, the factor of the highlights is diminished relying upon the dimensions of the convolutional and max-pooling veils. Be that as it can, the quantity of spotlight mapping typically accelerated for map the outstanding suitable highlights of the facts pics to perform better order precision. The yields of the final element maps of CNN are applied as a contribution to the completely related machine which is called the characterization layer. In the arrangement layer, the ideal quantity of highlights can be gotten making use of highlight preference techniques relying upon the detail of the load framework of the closing neural device, at that factor the chose highlights are set to the classifier to technique certain of the info photos. In view of the maximum multiplied truth, the classifier offers yields for the evaluating training that the data photos have an area with. Numerical subtleties of various layers of CNN are mentioned inside the accompanying segment.

CNN LAYER:

In this residue, the element maps of the past layer are convolved with learnable parts, for example, (Gaussian or Gabor). The yields of the piece revel in direct or non-directly enactment capacities, as an instance, (sigmoid, hyperbolic digression, softmax, amended immediately, and character capacities) to frame the yield spotlight maps. As a rule, it very well can be numerically tested as eq(1)

$$x_j^l = f \left(\sum_{i \in M_j} x_i^{l-1} k_{ij}^l + b_j^l \right) \quad \text{----- (1)}$$

Where x_j^l is the yields of the present layer, x_i^{l-1} is past layer yields, k_{ij}^l is a portion for the present layer, and b_j^l is the predisposition for the present layer. M_j speaks to a choice of info maps. For each steo, map is given an added substance inclination b . In any case, the info maps will be convolved with unmistakable pieces to create the relating yield maps. For a moment, the suitable maps of j and k both are summation over the information I which is specifically applied to the j^{th} bit over the info I and takes the summation of its and a similar activity are being considered for k^{th} piece also.

SUBSAMPLING LAYER

The subsampling layer plays a down sampling interest in the information maps. In this layer, the data and yield maps don't change. For instance, at the off hazard that there are N information maps, at that point, there may be really N yield maps. Because of the down sampling pastime, the dimensions of the yield maps can be diminished relying upon the dimensions of the down sampling veil. In this research, 2×2 down sampling cover is utilized. This activity can be figured as

$$x_j^l = f \left(\beta_j^l \text{down}(x_j^{l-1}) + b_j^l \right) \quad \text{----- eq(2)}$$

In which $\text{down}(\bullet)$ speaks to a subsampling ability. This capacity, for the most component, summarizes over $n \times n$ square of the maps from the past layers and chooses the ordinary well worth or the most increased qualities most of the $n \times n$ rectangular maps. Likewise, the yield manual measurement is decreased to n times regarding the two elements of the thing maps. The yield maps at long final enjoy directly or non-direct actuation capacities.

CLASSIFICATION LAYER

This is a completely associated layer that processes the score for each class of the articles utilizing the separated highlights from the convolutional layer. In this work, the size of the element guide is viewed as 3×3 and a feed-forward neural net is utilized for grouping. Concerning the actuation work, softmax capacity is utilized as recommended in many sorts of writing. 1st plan to compare the results with the previous works 2nd step will compare the accuracy/mean-squared error to see which is more effective, as well as compare the speed of proposed method using CDNN and the previous used techniques. Shanthi et al.[4] use pixel densities over various zones of the picture as to highlights for an SVM classifier. Their framework accomplished an acknowledgment pace of 82.04% on a manually written Tamil character database. K. Mohana Lakshmi et al. [3] achieved a recognition rate of 87.5% on Telugu character dataset using HOG features and Bayesian classification. Here I want to try to get accuracy greater than 90%. For this applying Convolutional Neural Networks which are more efficient than the methods used by the above authors

D. Data Preprocessing

The dataset contains images of contains approx 270 samples of each of 166 Telugu characters written by native Telugu writers. These images are in TIFF format and are unequally sized. The images were under the folders with the names of the writer and the image file name as its Unicode character. Here I changed the image filename as the writer name followed by the Unicode character so that each image will get a unique file name. And then all the images with the same Unicode were grouped under a folder with Unicode as its folder name so that I can use

load_files method in sklearn.datasets2 module. Then, the original unequally sized rectangular images are resized into 80 x 80 square images and saved them as JPG files. As mentioned in the Algorithms and Techniques, the classifier used to train the data is Deep Convolutional Neural Network. The input to the convolutional neural network is a 4D Tensor. The 80 x 80 image is reformatted into a 4D tensor with shape (samples, channels, rows, columns) which is then passed through a stack of different kinds of layers as follows:

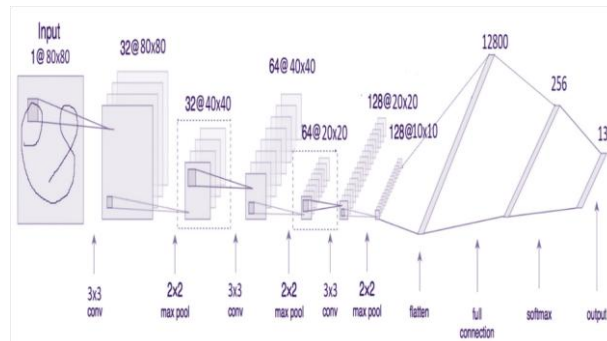


Figure: 6 HW character recognition

Information - 4D tensor with form (n, eighty, eighty, 1) where n is the variety of info pix and the variety of channels is 1 because the pix are double. (Number of channels = 3 if the pix are RGB). Show in fig.6

Layer 1 - Convolutional Layer with 32 channels and channel length 3 x 3 and Max pooling layer with channel length 2 x 2.

Layer 2 - Convolutional Layer with 64 channels and channel length three x three and Max pooling layer with channel size 2 x 2.

Layer 3 - Convolutional Layer with 128 channels and channel size 3 x three and Max pooling layer with channel length 2 x 2. Straighten() - It changes over the yield of the convolutional a part of the CNN into a 1dimensional factor vector, to be utilized by the absolutely related layer.

Layer 4 - Fully Connected layer (Dense) with 256 neurons, with a dropout regularization pace of zero.Four (likelihood of zero.4 that any given aspect might be dropped in the course of preparing).

Layer 5 - Fully Connected layer (Dense) with 138 neurons. Here, directly initiation RELU is applied for the convolution and max-pooling layers and SOFTMAX enactment is utilized for the yield layer (Fully Connected Layer).

Initially tried the images with size 32x32 When run the algorithm got very less accuracy, then started changing the optimizer. First used ADAM and tried for many combinations of learning rate and decay. Then tried ADADELTA and tried for parameter tuning, even though the performance didn't improve. Then went through the dataset (i.e., images) which were not clear with size 32 x 32 Then changed image size to 64 and then 80 Then noticed some repeated images with different label name which causing the algorithm to get very low performance. Then removed the similar images with different label names Then got 138 characters whereas initially have 166 characters when downloaded the data

from HP labs/mit website. finally performed and explored one-of-a-kind avenues concerning the accompanying speculation structures:

- Dropout in a convolutional layer
- Dropout in a completely associated layer
- Data manipulating
- Batch Normalization

Applying those methods did not provide a first-rate carry in execution. Then with 3 convolutional layers and ADAM as optimizer, got 88% test accuracy and 91% training accuracy. But, after changing optimizer to SGD with learning rate 0.1, and adding one more convolutional layer, training accuracy increased to 94% and the test accuracy increased to 91%.

VI. Model Evaluation and Validation

we got test accuracy of 91% and training accuracy of 95% on Telugu character dataset with 20 epochs, if we increase number of epochs, then the accuracy will increase further. The loss reduced from 4.03 to 0.4 as the training progressed. For the first few epochs, the training accuracy is less than the validation accuracy and then after some epochs, train accuracy increased. The validation curves were given in figure 4 for figure.7. The accuracy obtained by the model is greater than the benchmark reported earlier. It's likely that adding more epochs could increase the accuracy further.

The benchmark reported is 90% of test accuracy. But by running 20 epochs, the model obtained 91% accuracy and 95% training accuracy. By adding few more epochs, the accuracy may increase further. The following table shows the comparison between the accuracy obtained by the CNN model and other models used to classify handwritten Telugu characters.

కలమయరసన

Fig: Some of the characters used in this project

కొమ్మకొరిసేసే

Figure: 7 GUNITHAM and VOTHULU

This CNN model is applied on gunithalu and vothulu got good accuracy compared to existed work[5].

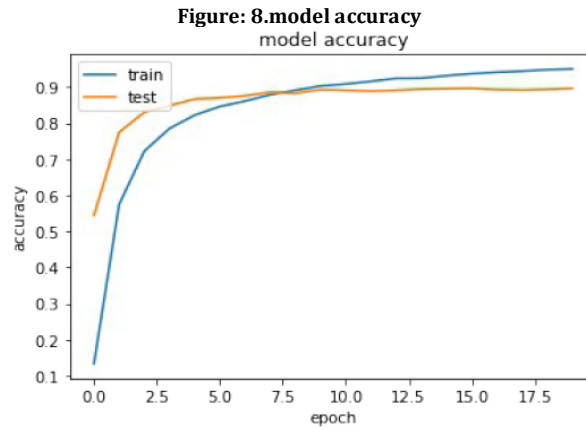


Fig.8 shows that accuracy related to test data and trained data, in this model compared test model trained model got more accuracy.

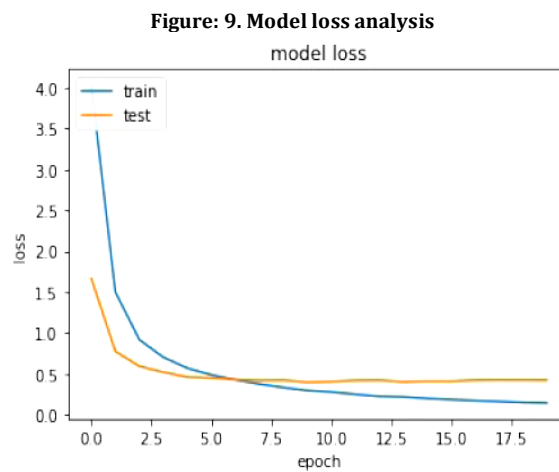


Fig.9 explains that loss parameter in this model loss of test data is more compared to trained model.

Table: 1 comparison of methods

METHOD	ACCURACY
CNN proposed	98.3%
ZF	78%
ADZM	88.8%
2D-FT_SVM	71%
MLP	85%
Bayesian	87.5%

Table :1.explains that CNN model achieves 98.3% accuracy this is good compared to all methods The accompanying table demonstrates the genuine marks and the predicted names of the

preliminary 50 snapshots which demonstrates the model is foreseeing practically right names apart from 2 or three out of fifty pictures

Table :2unicode relations

Original	Tested	Original	Tested
47	47	110	110
46	46	134	134
60	60	67	67
68	68	59	59
121	121	65	65
15	15	119	119
119	119	72	72

Table: 2 explains that Disarray Matrix is applied to test the exhibition of the neural system grouping.

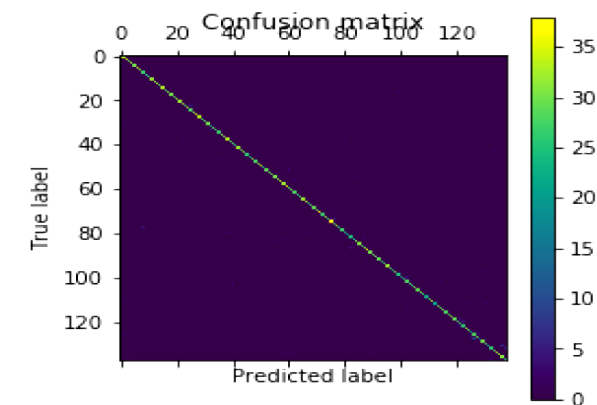


Figure: 10. Predictive label

Fig.10 Demonstrates the plot of the perplexity grid for the model used to reserve written by using hand Telugu Characters.

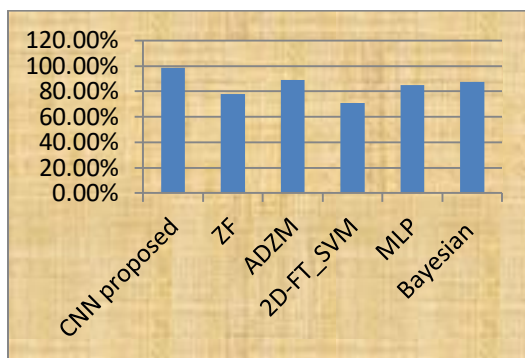


Figure: 11. Graphical view

Figure: 11. Explains about graphical representation of accuracy here CNN got 98.30% accuracy which is more efficient recognitions in TELUGU GUNITHAM and VITTULU.

VII. CONCLUSION

It is well known that the deep convolutional neural networks are very good at classifying image data. There were many experiments done on handwritten character recognition using convolutional neural networks for English alphabets, numbers, Chinese, Arabic and some of the Indian languages like Hindi, Devanagari script etc., But there is very less contribution on Telugu language character recognition. Due to very less contribution, the data available on internet is not so good. In this didn't notice that initially and faced many problems with repeated data. found that the problem was in data, then deleted the repeated ones and made the data clear. Then found difficult in tuning the algorithm tried different optimizers with different learning rates and tried a model changing number of layers and number of filters and filter size. Finally, ended up with a model that gives 98.3% accuracy which exceeded my expectations to get around 85 to 98.3%

VIII. FUTURE SCOPE

The OCR implementation has been covered with the help of neural networks, with this 98.3% accuracy is obtained. This implementation is very useful for south India online, offline Telugu character recognition system. The previous system for Telugu OCR character level recognition using x and y direction histogram model had been implemented. But, got less accuracy so our proposed work achieves better accuracy with the help of CNN. The machine learning algorithms like SVM, logistic regression can gives the better accuracy compared to CNN. Therefore the online and offline character recognition system of Telugu need to implement using machine learning

algorithms by SVM, LR gives the more accuracy and less skew corrections. This application spanned using android, IOS, RIM can gives the easy access, this ML, neural network algorithms by using segmented data and Telugu dataset guninatham and vothu together gives the better accuracy. The implemented system also useful for other languages like Tamil, kanada, Malayalam, etc OCR systems all languages of India.

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