ABSTRACT
Malayalam, the official language of Kerala, a southern state of India has been accorded the honour of language of eminence. Hence the researches in recognition and related works in Malayalam language is gaining more prominence in the current scenario. This paper proposes the use of Curvelet transform and neural network for the recognition of handwritten Malayalam character. Curvelet transform is to be used in the feature extraction stage and neural network for classification. Curvelet transform provides a compact representation for curved singularities and is well suited for malayalam language. Two different back propagation algorithms had been employed and the performance is compared on varying architecture. The promising feature of the work is successful classification of 53 characters which is an improvement over the existing works. Application of character recognition include sorting of bank cheques and postal letters, reading aid for blind, data compression etc. Besides, an automated tool with graphical user interface in MATLAB has been developed for Malayalam character recognition.

General Terms
Pattern Recognition, Artificial Neural Network (ANN), Curvelet Transform, Optical character recognition (OCR).

Keywords
Malayalam, Character Recognition, Artificial Neural Network (ANN), Curvelet Transform, Handwritten.

1. INTRODUCTION
The overwhelming volume of paper-based information on companies and offices challenges their ability to manage documents and records. Since computers can work much faster and more efficiently than human. It is used to perform many of the tasks required for efficient document and content management. But computer knows only alphanumerical characters as ASCIIcode. So computer cannot distinguish character or a word from a scanned image. In order to use the computer for document management and automatic sorting of mails etc., it is required to retrieve alphanumerical information from a scanned image. Optical character recognition system (OCR) aims to convert a document into electronic text, which can edit and search etc. At present, more sophisticated optical readers are available for English, Roman, Chinese, Japanese and Arabic text. In the United States, about 60% of the handwritten is sorted automatically. At the same time the OCR in Malayalam is at the beginning stage.

Malayalam is a Dravidian language with about 35 million speakers. It is spoken mainly in the south western India, particularly in Kerala. Until the 16th century Malayalam was written in the vatteluthu script. Modern Malayalam script is derived from the Grantha script, a descendant of the ancient Brahmi script. Malayalam is written from left to right. There are fifty-three letters, called akaras [1]. As a result of the difficulties of printing Malayalam, a simplified or reformed version of the script was introduced during the 1970s and 1980s. The main change involved writing consonants and diacritics separately rather than as complex characters. These changes have not been consistently so the modern script is often a mixture of traditional and simplified letters [2]. The character set consists of 13 vowels, 2 left vowel signs, 7 right vowel signs, consonants, and diacritics.

Character recognition or optical character recognition (OCR) is the conversion of scanned or photographed images of typewritten or printed text into computer readable text. Optical character recognition has become one of the most successful applications of technology in the field of pattern recognition and artificial intelligence. Character recognition has a wide range of applications in banking and post office etc.

1.1 Motivation
Now days Information Technology based applications are growing rapidly and with the increase in these applications there is need of character recognition. Applications of character recognition are sorting of bank cheques and postal letters, reading aid for blind, Data compression etc.

In the field of Malayalam optical character Recognition very few works have been reported so far. One reason for this Malayalam language is rich in patterns while the combinations of such patterns make the problem even more complex.

1.2 Optical Character Recognition
Optical Character Recognition (OCR) is the one of the most successful application in the field of pattern recognition and artificial intelligence. It deals with recognizing optically processed character. Optical character can be performed either in off-line or on-line. In off-line method recognition is done after writing or printing has been completed while in on-line recognition is done at the same time as character is drawn or print. For these systems to effectively recognize by hand-printed or machine-printed forms, individual characters must be well separated.

Fig. 1 shows different areas of character recognition [3]. The performance of an OCR is mainly depend on quality of input document. With regard to recognition accuracy, constrained or printed character, have higher performance than for unconstrained character.
2. MALAYALAM CHARACTER RECOGNITION -A REVIEW

Some of the existing techniques used in OCR for Malayalam, the official language of Kerala a state in India. NAYANA™ OCR developed by CDAC is based on the Feature Extraction method of character recognition. It uses an Otsus algorithm based thresholding approach for converting grey scale image to binary. Skew detection is done using the Projection profile. Another work for recognition of unconstrained isolated handwritten character recognition by G. Raju. In this paper samples are selected at 256 x 256 without any preprocessing such as denoising and thinning. The image is converted to inverted binary and wavelet transforms are applied using the wavelet DB4. For each sub band zero-crossing is used as feature for classification [4]. A Novel Bilingual OCR for Printed Malayalam-English Text based on Gabor Features and Dominant Singular Values is proposed by Bindu Philip R. D. Sudhaker Samuel. Which uses Gabor features and two stage classification approach. They reported a recognition rate of 96.5% [5]. Another method by Renju John and G. Raju and D. S. Guru it uses image of size 32 x 64 and wavelet transform is used to find feature vector. 1-D Wavelet transform of horizontal and vertical projection issued as feature vector. A Multi-Level Perceptron network issued for classification [6]. Another work is done by M. Abdul Rahman and M. S. Rajasree uses horizontal and vertical scanning for separating lines in a document and for words in a line. For separating combinational letters like , labeling image based method is used. Labeling is done by the four and eight connected pixels of an image for getting label and , Wavelet multi-resolution analysis for the purpose extracting features, Daubechies (db4) wavelet is used. Artificial Neural Network is used to accomplish the recognition tasks [7].

3. THE OCR SYSTEM

Optical Character Recognition (OCR) is the conversion of scanned or photoded images of typewritten or printed text into machine-encoded/computer-readable text. A typical OCR system consists of several components. In Fig. 3 a common setup is shown.

![Image Scanner](Image 111x211 to 223x273)

Fig. 3: Block diagram of typical character recognition system

The first step in the process is to digitize the document. Optical scanners are used to digitize which generally consist of a transport mechanism plus a sensing device that converts light intensity into gray-levels. Image scanning is done to get the digital form of character on a page or paper, usually this scanning is done at a minimum of 300 dpi resolution. Their resolution at which the scanning is done plays a crucial role in accuracy of character recognition.

The image resulting from the scanning process may contain certain amount of noise. Depending on the resolution on the scanner and the success of the applied technique for thresholding, the characters may be smeared or broken. Some of these defects will later cause poor recognition rates. These noises can be eliminated by using a preprocessor and we can smooth the digitized characters. Preprocessing is done to enhance the scanned images, by using binarization, noise removal, skew correction etc.

At Character recognition phase, first the line is extracted and word is extracted from the scanned document. Usually the horizontal projection method and vertical projection methods are used for extracting line and word in a document. In order to detect each character, usually connected component method is used. These extracted characters used for feature extraction and further steps.

![Character recognition](Image 54x655 to 280x770)

Fig. 1. The different areas of character recognition

![Typical Malayalam Character](Image 151x334 to 168x346)

Fig. 2. A Typical Malayalam Character

Bindu Philip and R. D. Sudhaker Samuel works on An Efficient OCR for Printed Malayalam Text they used SVM classifiers and used a novel algorithm for segmentation. They considered that printed malayalam character have three segments as shown in Fig. 2. The first segment could have either of one left vowel sign or two left vowel sign, the second segment it is core it can be either vowel or consonant. The third segment is right vowel sign. If we consider X as consonant and Y as vowel, 0 as left vowel sign and 1 as right vowel sign we can have X, Y, 0X, 00X, 0X1, X1 form of valid character sequences. For recognition five features are used and is classified using SVM classifier [8]. Another work by Abdul Rahman, M. S. Rajasree uses number of horizontal and vertical line as feature for recognition of characters [9]. Ashutta T. Jia, Yahkoob Ayappally, and Syama K. uses N - gram segmentation approach and used along with geometric feature extraction. They uses these feature for SVM based classification [10]. Jomy John, Pramod K. V, and Kannan Balakrishman proposed a method for offline handwritten Malayalam character recognition it uses chaincode and image centroid as a feature. Uses a median filter for noise removal. Otsu’s global thresholding for binarization [11].
Recognition phase involve two step:

1) Feature extraction and feature selection
2) Classification

Features chosen has to satisfy the condition 1) small intraclass variance 2) large inter-class variance. This means that features extracted from samples of the same class should be similar, while that of different classes should be dissimilar.

These features are used for recognition stage. Recognition is achieved using artificial neural network. Before neural network is used for recognition it has to be trained properly with character database. After neural network is trained features from the character to be recognised are given to the input of the neural network. From the previous training experience the neural network will classify the character to one of 53 Character.

4. PROPOSED MALAYALAM CHARACTER RECOGNITION

The first step is the creation of a data base for Malayalam characters. Since no standard data base is available a set of samples are collected from persons having different age and sex group. A database is created such a way that 53 characters to be recognised are written over a white A4 size paper. 53 characters consist of 8 vowels and 36 consonants. Vowels are numbered from 1 to 8, consonant are numbered from 9 to 44 and 45 to 53 are conjuncts. These samples are scanned using Canon MF4820D. Scanning is done at a resolution of 300 - 400 dpi. Samples are made with a white background. Then each character is segmented and stored in different folders with some unique id’s to represent each character as shown Fig. 5. The folder name Malayalam script database contains 53 folder corresponds the each character. Each character folder contains 40 samples of character. The scanned image of Malayalam character ‘Ah’ is shown in Fig. 8 which is the intensity (Gray Scale) image and is further passes through following preprocessing stages.

- Noise Removal
- Binarization
- Thinning
- Normalising the size of image
The noise present in the scanned images are Gaussian noise and salt and pepper noise. Gaussian noise can be suppressed by median filtering.

The next step of preprocessing is binarization. The filtered scanned image is a grayscale which has 256 intensity levels, which is converted to a binary image having 2 level intensities, white and black image using Ostu’s global threshold method. A fixed threshold is used, where gray-levels below this threshold is said to be black and levels above are said to be white. Fig. 9 shows the binary image after global thresholding method.

![Fig. 9. binarized image of malayalam letter 'ah'](image)

The binary image after thresholding has pixel value such that white pixel has logic ‘1’ and black pixel has ‘0’. For further steps the image is then inverted to make pixel value correspond to the character to ‘1’.

Form the inverted image connected pixels less than some threshold (say 30 pixels) is removed which corresponds to noise as shown in Fig. 10.

![Fig. 10. inverted binarized image of malayalam letter 'ah'](image)

Further a bounding box is created which touches the character in four sides. It removes unnecessary black spaces as shown in Fig. 11.

![Fig. 11. Cropped image](image)

Then the image is resized to $32 \times 64$. Then perform thinning operation is performed to make each character pixel to ‘1’ - pixel width. Fig. 12 shows a thinned image of the Malayalam character ‘ah’.

![Fig. 12. Character after performing thinning operation](image)

So, after preprocessing a thinned image of character resized to $32 \times 64$ is obtained. Which is suited for further processing.

### 4.2 Feature Extraction

Feature extraction is the most important step in character recognition. Feature extraction is a special form of dimensionality reduction. Feature extraction reduces amount of resources required to describe a character. In this case the final output is preprocessing of size $32 \times 64$ ($=2048$ bits) by finding out a feature we can represent the same character by lesser number of bits.

Feature extraction involves two steps

1) Obtaining projection profile
2) Computing transformation

In proposing method projection profile of $32 \times 64$ size character image taken. Basically two types of projections are used: horizontal and vertical. Projection profile is a data structure used to store the number of non-background pixels when the image is projected over the normal X-Y axis. Each cell of the projection vector is associated with the number of pixels above a predefined threshold (usually background color). A row vector of size 32 as horizontal projection profile and a row vector of size 64 as the vertical projection profile is obtained as shown in Fig. 13.

$$Vertical\ Projection(x) = \sum_{r=1}^{32} A_{r}$$  

(1)

$$Horizontal\ Projection(x) = \sum_{c=1}^{64} A_{c}$$  

(2)

Where A is a black and white image with character having white pixel. Value of r ranges from 1 to 32 and values of c ranges from 1 to 64.

![Fig. 13. Projection profile of typical character 'ah'](image)

After projection profile of a character is obtained. Curvelet Transformations are used to compute features.

### 5. Feature Extraction Using Curvelet Transform

The main contribution of the work is the use of curvelet transform for feature extraction. It had been chosen since Malayalam language possess many curved singularities and curvelet provides an efficient representation. The Curvelet transform is a higher dimensional generalization of the Wavelet transform. By using Curvelet Transform, curved singularities can be well approximated with very few coefficients [12]. Curvelet transform uses translations, dilations, and rotations of basic curvelet $\psi$. Curvelet transform has a highly redundant dictionary which can provide sparse representation of signals that have edges along the regular curve. Conceptually, the curvelet transform is a multiscale pyramid with many directions and positions at each length scale, and needle shaped elements at fine scales [13].

For the implementation of curvelet transform, first 2D Fast Fourier Transform (FFT) of the image data is taken. Then the 2D Fourier frequency plane is divided into wedges (like the shaded region in Fig. 14). The parabolic shape of wedges is the result of partitioning the Fourier plane into radial (concentric circles) and angular divisions.
The concentric circles are responsible for the decomposition of an image into multiplescales (used for band passing the image at different scales) and the angular divisions partition the band passed image into different angles or orientations. Thus if we want to deal with a particular wedge well, need to define its scale $j$ and angle $l$. Now let’s have a look at the spatial domain (Fig. 14 right). Each of the wedges here corresponds to a particular curvelet (shown as ellipses) at a given scale and angle. This indicates that the inverse FFT of a particular wedge, if taken, will determine the curvelet coefficients for that scale and angle. Curvelet obey scaling law, i.e., $\text{length} = \text{width}^{\frac{1}{2}}$.

There are two different ways of digital implementations of Fast Digital Curvelet Transform (FDCT).

1) Curvelets via USFFT (Unequally Spaced Fast Fourier Transform)
2) Curvelets via Wrapping

In this work, feature extraction is done using Curvelets via USFFT are used. Digital Curvelet transform is obtained by

$$C^D(j, k, l) := \sum_{0 \leq s_1, t_2} f[t_1, t_2] \psi^D_j, k, l[t_1, t_2] \tag{3}$$

$C^D(j, k, l)$ is the output of curvelet transform. From the Fig. 15, a, b, c are the curvelets at different direction or angle. In the figure, the curvelet named c which is perfectly aligned with the curved edge and there for it have large coefficient value. Curvelet a, b will have a low coefficients value close to zero. Since they are far from the alignment [14].

### 5.1 Comparison with wavelet

Fourier series requires a large number of terms to reconstruct a discontinuity good accuracy. Wavelets transform have the ability to solve this problem of Fourier series, as they are localized and multiscale. However, though wavelets do work well in one-dimension, they fail to represent higher dimensional singularities (especially curved singularities). At the same time, curvelets can model such curved discontinuities well. The main idea here is that the edge discontinuity is well approximated by curvelet transform and is shown Fig. 16.

5.2 Feature extraction using curvelet

Following steps are involved in computing feature vectors using curvelet transform.

1) Compute Fast discrete cosine transform of the character
2) Extract Coarse Curve Coefficient
3) Find projection of Coarse Curve Coefficient
4) Feature vector is formed by concatenating both projections

5.3 Curve Lab

The software package CurveLab used in this paper for feature extraction, and is available at http://www.curvelet.org.

6. CHARACTER RECOGNITION USING NEURAL NETWORK

After feature extraction, next step is to character recognition. Character recognition is done using a multi-layer perceptron. Before neural network is used for recognition it has to be trained properly with character database. After neural network is trained, features from the character to be recognised...
are given to the input of the neural network. From the previous training experience the neural network will classify the character to one of 53 characters.

Artificial neural networks (ANN) are the result of academic investigations that use mathematical formulations to model nervous system operations. The aim of neural networks is to mimic the human ability to adapt to changing circumstances and the current environment. This depends heavily on being able to learn from events that have happened in the past and to be able to apply this to future situations. In common with biological neural networks, ANNs can accommodate many inputs in parallel and encode the information in a distributed fashion.

Artificial neural networks consist of many nodes, i.e. processing units analogous to neurons in the brain. Each node has a node function, associated with it which along with a set of local parameters determines the output of the node, given an input. The neural net can generally be a single-layer or a multilayer net. Fig. 17 shows the block diagram representation of multilayer ANN [15].

![Fig. 17. Block Diagram representation of 3 layered MNN](image)

### 6.1 Architecture of Neural Network

The architecture of Artificial Neural Network is shown in Fig. 18. It consists three layers named input layer, hidden or middle layer and output layer and the neurons are arranged along these layers.

![Fig. 18. Feed forward network with 3 layer](image)

It consists three layers named input layer, hidden or middle layer and output layer and the neurons are arranged along these layers. Number of nodes in the input layer depend on feature vector and in output depend on classes of character. Neural network comprises many processing elements known as neuron and these neurons receive several signals from its input links process it and sends to other neurons through output links. The neuron computes the weighted sum of input signals. The mathematical equation for this is given below.

\[ X = \sum_{i=1}^{n} x_i w_i \]  

(4)

Where \( x \) is neuron associated weight \( w \).

Then the weighted sum is compared with a threshold value. If the net input is less than the threshold value, the neuron does not activate and if the net input value is greater than or equal to the threshold, the neuron becomes activated.

\[ Y = \begin{cases} +1 & \text{if } X \geq 0 \text{ is even} \\ -1 & \text{if } X < 0 \text{ is even} \end{cases} \]

(5)

Here \( \theta \) is threshold [16]. The above transfer or activation function is called sign function. Four common types of activation of neural network used in practical applications were step, sign, linear and sigmoid function as shown in Fig. 19.

![Fig. 19. Activation functions of a neuron](image)

### 6.2 Back propagation Algorithm

The training algorithm of backpropagation involves four stages. Numerous different learning algorithms are available to train the neural network but the most popular one is Backpropagation. Learning in MLP is similar as Perceptron. The input patterns are applied to the input layer of the network and these patterns are processed by input layer and passed to the next layer. In this way these patterns propagate layer by layer until the output pattern is generated by output layers.

If the output pattern is different from the desired one, error is calculated and propagates backwards through output layer to the input layer. The weights are modified as the error propagated.

A neuron determines its output and computes the net weighted input

\[ X = \sum_{i=1}^{n} x_i w_i - \theta \]  

(6)

Where \( n \) is number of neurons and is threshold applied on neuron.

\[ Y_{\text{sigmoid}} = \frac{1}{1 + e^{-x}} \]  

(7)

The error signal at the output \( k \) at iteration \( p \) is defined by

\[ e_k(p) = t_k(p) - y_k(p) \]  

(8)

weight in each layer will update based on the error as

\[ w_{jk}(\text{new}) = w_{jk}(\text{old}) + w_{jk} \]  

(9)

As a result of weight update the neural network tries to reduce error. Two different training algorithms is used there as Levenberg-Marquardt backpropagation and Bayesian Regularization backpropagation.
6.2.1 Levenberg-Marquardt backpropagation
The Levenberg-Marquardt algorithm uses an early stopping criterion to improve network training speed and efficiency. To determine the criterion, all the data are divided into three sets. The first set is the training set for determining the weights and biases of the network. The second set is the validation set for evaluating the weights and biases and for deciding when to stop training. The validation error normally decreases at the beginning of the training process. When the network starts to over-fit the data, the validation error begins to increase. The training is stopped when the validation error begins to increase and the weights and biases will then be derived at the minimum error. The last data set is for validating the weights and biases to verify the capability of the stopping criterion and to estimate the expected network operation on new data sets.

6.2.2 Bayesian Regularization
Bayesian regularization is a modification of the Levenberg-Marquardt training algorithm to improve the models generalization. Overfitting problem or poor generalization capability happens when a neural network over learns during a training period. As a result, such a too well trained model may not perform well on unseen data set due to its lack of generalization capability. This approach involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set (MSE or $E_n$) [17].

Training stops when any of these conditions occur:
- The maximum number of epochs (repetitions) is reached.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min grad. $\mu$ exceeds $\mu$ max.
- Validation performance has increased more than max fail times since the last time it decreased (when using validation).

7. RESULTS AND DISCUSSIONS
The experiment is done using Matlab R2013a on a computer having Intel i3 processor and 6 GB RAM. In the experiment, the trained network using 40 samples of each 53 classes and atotal of 1760 (40 $\times$ 53) samples. The trained network is tested using 10 samples of each classes. Find out system performance changing the transformation technique in feature extraction. Curvelet transform is used for feature extraction. The performance of the system for these features will explain the detail. Extracted feature using these techniques is used for train neural network. Neural network used are feedforward net with logsig activation function at hidden and output layer as in Fig. 20.

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7.1 Performance for Curvelet based feature
When curvelet transform is used for feature extraction, recognition accuracy of 80.79% is obtained. Since there is no inbuilt toolbox in Matlab to compute curvelet transform, ACurveLab [12] tool box by candes is used.

Feature extraction steps adopted discussed in the early section 5.2.

Feature vector of dimension 64 is used for classification. Table I shows result that has obtained.

Fig. 20. Artificial Neural network used for recognition
Number of inputs of a neural network depend on size of feature vector and the number of nodes at output depends on number of classes.
### 7.2 Graphical User Interface

A graphical user interface created using Matlab GUI creator. Gui created is shown in the Fig. 21 The character to be recognised is loaded by clicking the button load image.

![Fig. 21. Graphical User Interface](image)

The image in the left side shows the loaded image and the image on the right side shows a preprocessed image. The detect character will show in file detected.txt file. Also A pop message also appear which contain the id and character recognized is shown in Fig. 22.

![Fig. 22. Detected character in pop-up window](image)

The start training ANN button will start the training of neural network and attain the weights in each node.

### 8. CONCLUSION AND FUTURE WORK

Current status of OCR in Malayalam language has been reviewed. A Malayalam character recognition system is proposed using Curvelet transform and neural network. A graphical user interface is also created for the proposed system using Matlab. The proposed system is successful in classifying 53 isolated characters. Future work aims at the reduction of dimension for the feature vector.

### 9. REFERENCES


