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An Intelligent Handwritten Malayalam Text Recognition Using Optimized Machine Learning Based Optimization Frameworks

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Abstract

Traditional Machine Learning (ML) and Deep Learning (DL) models are failed to predict the characters, overlapping sentences and diacritical marks. Because Malayalam has various basic compound characters which are more than 50. Also, generalization is failed with handwriting variations for different individuals. In some cases, frequent misclassification is occurred due to the similar characters. Moreover, larger training dataset has required higher computing power so, the efficiency was degrading. Therefore, to develop an intelligent framework which is used to extracts the Malayalam text from the images. To improves the pre-processing stage by adding the entire steps such as normalization, binarization, augmentation and noise removal. To overcome the Malayalam script complexity such as visually same characters, diacritical marks, etc. This paper develops a novel Bayesian Neural Network based Hybrid Cuckoo Search with Lyrebird (BNN-HCSL) algorithm to enhance the character recognition efficiency. Moreover, the developed BNN-HCSL replica was implemented on MATLAB platform and the comparative analysis was performed in terms of performance matrices such as accuracy, precision, recall, F-Measure and Word Error rate (WER) to analyse the effectiveness of the prediction. Moreover, the attained outcomes are demonstrates the better for proposed model in attaining accurate and scalable Malayalam handwritten image to text recognition. Also, this study has contributes the document digitization by accessing the Malayalam handwritten contents.

Keywords: *text recognition, Machine Learning , Deep Learning, generalization*

1. Introduction

Handwritten character recognition is one of the challenging research domains of artificial intelligence as well as pattern recognition [1]. Malayalam, a Dravidian language, is among the most under-resourced languages and up to 15th century it was considered as Tamil dialect [2]. Moreover, the language has used multiple scripts, containing Tamil scripts like Vatteluttu and Pallava Grantha. Consequently, Malayalam is unique among all Indian languages since it incorporates both Tamil which is termed as Dravidian language and Sanskrit which is termed as Indo-European language grammar. Moreover, it highlights under 'Chandrakkala' and 'Chillu', which are not written but articulated when speaking in Tamil and do not exist in Indo-European languages [3]. The Malayalam language is spoken by the people of Kerala State in India [4]. After the pandemic situation created by the novel coronavirus, it has become a necessity to encode the local language, conventionally written in pen and paper, in an electronic format [5]. Optical character recognition (OCR) systems convert handwritten documents to a computer-editable digital form [6]. This is highly beneficial for individuals to share documents among different offices, banks, and teacher notes when conducting online classes in the local language. Malayalam is a language with a rich character set and it is written from left to right. Some of the vowel diacritics in the language extend above or below the full length of a normal alphabet. The language contains compound letters formed of two different characters. The characters have a looped and curved nature. Some characters, like 'Chandrakkala', in the language are written with a space above another character. Because of the large variations in handwriting styles, large gaps are created above or below the characters where such letters are written. All these factors make the recognition of handwritten documents in this language a complex problem [7].

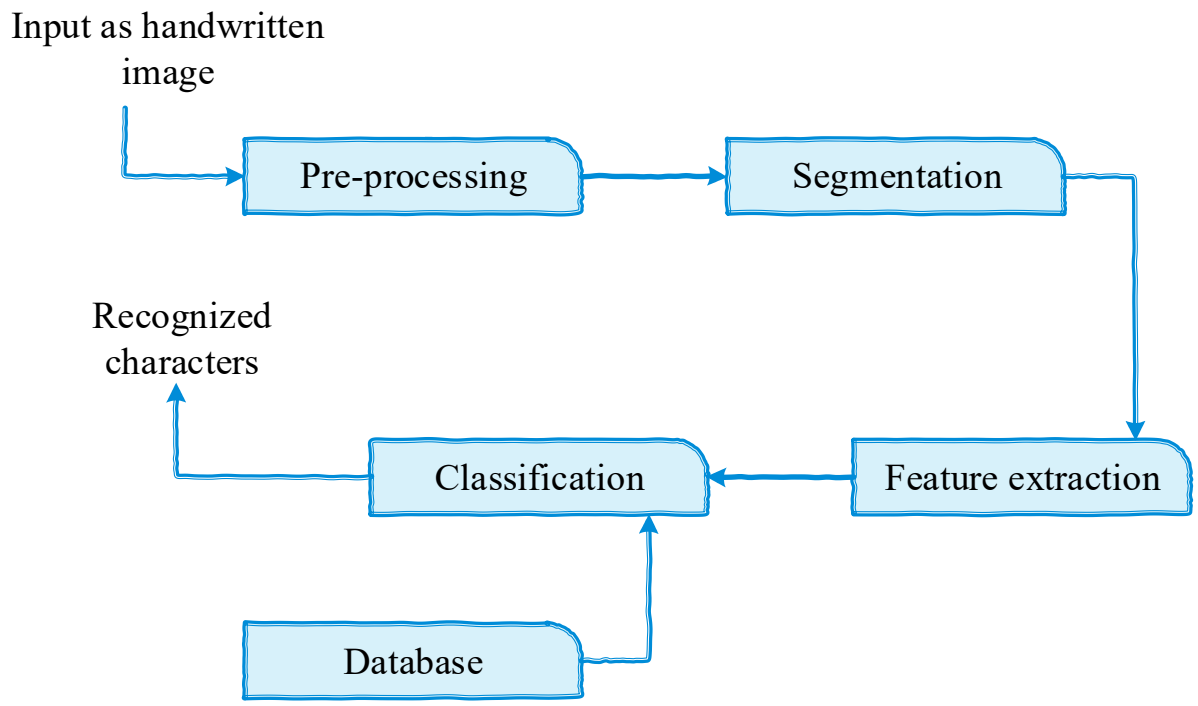


Fig. 1 Basic representation character recognition

Machine learning has advanced significantly in recent years, notably in the field of character recognition. The rising use of digital devices and the growing demand for efficient data processing have made HCR research crucial [8]. Character recognition involves several crucial steps, including preprocessing, segmentation, feature extraction, and classification. These successive actions work together to extract useful data and refine image characteristics [9]. Every stage's output flow into the next with ease, generating a dynamic process where data is gradually improved [10]. This methodical process guarantees that the original raw input goes through a number of changes, each of which adds to a more complex comprehension of the image characters [11]. The cooperative character of these steps from image correction to feature extraction optimizes the character recognition process as a whole, producing precise and effective classification outcomes. Figure 1 shows Block Schematic for the General Character Recognition Program [12].

The foremost challenge confronting Malayalam language OCR pertains to the intricacies of segmentation due to overlapping characters in handwritten text [13]. Most of the research endeavors primarily concentrated on parsing printed or character-based text, failing to effectively address word-level segmentation issues [14]. In response, we have pioneered a segmentation algorithm finely tuned to dissect words with remarkable precision and preserve the important features of the words thereby substantially enhancing segmentation efficacy.

Moreover, navigating the landscape of feature extraction in Telugu OCR presents a formidable complexity [15].

Numerous researchers have delved into diverse models for feature extraction, often grappling with unwieldy parameter sets [16] or declined recognition rates [17]. Recognizing the inherent advantages of CNNs [18] in feature extraction we have strategically embraced the SqueezeNet neural network. Renowned for its slender architecture, SqueezeNet [19]facilitates streamlined feature extraction without compromising accuracy, thus culminating in a notable advancement in the realm of Malayalam OCR [20]. Additionally, the important key concepts of the proposed technique are detailed below,

- Initially, a Malayalam handwritten images was collected from own and trained in the particular implementation system.
- Moreover, design an BNN-HCSL optimization framework for developed to accurately recognising the Malayalam languages from the collected images. .
- Then, input images are initially updated to the preprocessing to remove the redundant information from the images using filtering techniques.
- After that, segmentation and feature extraction was performed based on the CCAFA for extracting relevant features and segmenting the words from the images.
- Then update, the segmented output into the developed model BNN, which detects the Malayalam characters by applying the HCSO search fitness functions.

The manuscript's organization is as follows: section 2 and section 3 describe related works and problem statements. Section 4 elaborated on the proposed methodology, and section 5 discussed the results and discussion of the proposed technique with other papers. Finally, section 6 is ended with a conclusion and future scope.

2. Related works:

To address the handwritten text recognition issues, Banavatu, Triveni et al, [21] have developed the Adaptive DeepNet framework to identify the characters and Shuffle Net based Bidirectional long short term memory network was used as accurate prediction result purposes. Here, the south Indian languages such as Kannada and Telugu handwritten data source were collected from databases. Also, lyrebird optimization fitness model is combined to enhance the prediction accuracy. The simulation outcomes are demonstrated that the proposed model has

better performance while comparing other models. However, wider range of dataset cannot suitable because here two languages are simultaneously used.

To transform the Telugu handwritten document in to the various electronic documents S. Thara, et al, [22] have developed the custom DL model. This model has effectively enhance the model performance for applying the cosine similarity function. Also, the developed model consists three convolution blocks and max-pooling layers to solve the Telugu script identification. Then two dense and skip layers and four dropout layers are aligns the transforming function with respect to the training models. Moreover, this model was trained more than 50 Telugu characters and it was validates with various Chinese Arabic language transforming models. From that comparison it takes too much time for conversion as well as testing the each characters.

Haldorai, et al, 23 have developed the novel transfer learning based Inception-v3 to perform the automatic identification of Tamil handwritten text. Also, the model is combined with modified Radam optimizer to achieve the better outcome in terms of spell error detection and correction functions. Here, the handwritten Tamil texts are converted into the English language. Also, the verifications are done under the perceptron and modified Radam optimizer. Nevertheless, the words segmentation may difficult to finding the slants, widths and spacing of the each characters.

Optical Character recognition (OCR) is one of the most popular language recognition fields, which is more complex for some laid literatures. Therefore, this paper Lincy, Babitha, et al, [24] have introduced a Self-Structured lion optimization based convolution network to perform the precise recognition. Also, pre-processing and recognition function was performed under the convolution network layers with respect to the grayscale transformation and binarization. Then histogram mathematical function was enabled to classify probability of each Tamil characters from the images. Here, Tamil handwritten characters are effectively recognised and performs the state of art comparison was done. However, the character overlapping and stroke touching can makes the inaccurate segmentation.

In an pattern recognition, character recognition was important research fields, thus Devi Priya, Karthikayan et al, [25] have suggested the Self Adaptative transfer learning based lion optimization algorithm to produce the desired accuracy if each characters. Here, the ancient stone images are taken to analyse the Tamil languages and compared with other languages recognition techniques. This model has accurately predicts the curves, loops and holes from that collected stone images. Finaly, it serves the effective designs for preserving the stone inscriptions and preserving Tamil language as the traditional knowledge. But, large cale

datasets was not supported for this study because, it cannot balance the characters representations at every stages.

Table. 1 Research gap of existing study

Sl.no	Author name and references	Developed techniques	Functions	Merits	Demerits
1	Banavatu, Triveni et al, [21]	Adaptive DeepNet framework to identify the characters and Shuffle Net based Bidirectional long short term memory network	Kannada and Telugu handwritten data	proposed model has better performance while comparing other models	wider range of dataset cannot suitable
2	S. Thara, et al, [22]	custom DL model	Telugu script identification	this model was trained more than 50 Telugu characters and it was validates with various Chinese Arabic language	comparison it takes too much time
3	Haldorai, et al, [23]	novel transfer learning based Inception-v3	handwritten Tamil texts are converted into the English language	Very good performance during the training and testing time	words segmentation may difficult to finding

4	Lincy, Babitha, et al, [24]	Self-Structured lion optimization based convolution network	Tamil characters from the images	Tamil handwritten characters are effectively recognised	inaccurate segmentation
5	Devi Priya, Karthikayan et al, [25]	Self Adaptative transfer learning based lion optimization	the ancient stone images	it serves the effective designs for preserving the stone inscriptions and preserving Tamil language as the traditional knowledge	it cannot balance the characters representations at every stages.

Malayalam handwritten character identification is the most difficult task in OCR, and various research scholars have been working on a variety of languages. This is a one of the most important fascinating challenges since these handwritten characters haven't been resolved yet. Moreover, Tamil is the oldest of all the various languages, yet it is also the most difficult to identify for numerous techniques. The creation of an effective system has been the subject of extensive research in recent years. The phenomena of feature extraction and selection, and finally classification process can serve as the underpinning for the majority of character recognition research studies in the above reviewed literatures.

3. System model and problem statement

Handwritten language recognition model has starts with input Malayalam handwritten images and applying the filtering process to filters the input raw data for preparing the further stages [26]. Then, segmentation is enabled to separates the meaningful features from the data and process the for recognition using standard ML models. But, the model has founds the problems, which are effectively collaboratives the entire system, which are shown in figure.2.

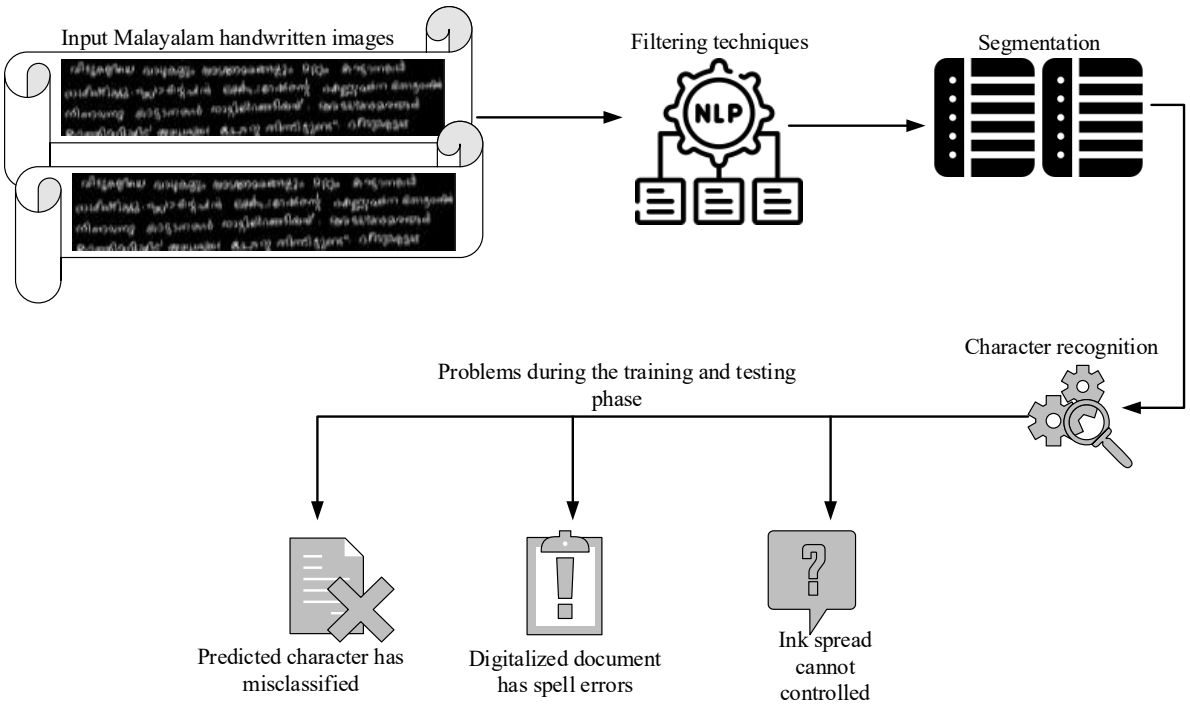


Fig.2 language recognition with their problems

Malayalam handwritten language recognition is one of the challenging research domain de to the complexity findings and recent ML models [27]. Consequently, Malayalam language has various characters such as diacritical notations, vowels, consonants, etc. So the script complexity may occur for frequent miss classification as well as similar character identification [28]. Furthermore, prediction accuracy is lacks due to the writer variation with respect to the inter and intra connection systems, this has termed as handwriting variability. data quality issues can mitigates the performance predictions and affected by variety of blurring and nose skew functions [29]. In some has the model has inefficacies due to the larger datasets, higher computational resources and visually misclassified characters [30]. Therefore, to address these issues an optimized ML based optimization frameworks was developed to mitigate the script variation and complexity issues.

4. Proposed Methodology

An intelligent Malayalam handwritten image character recognition replica is proposed in this article. Moreover the developed approach has two main phase like segmentation and recognition which is done using the manually written Malayalam documents images. Conseqiently, the manually created document has verbal, consonants and numerals. Also, the developed Malayalam handwritten image character recognition model was illustrated in fig.3.

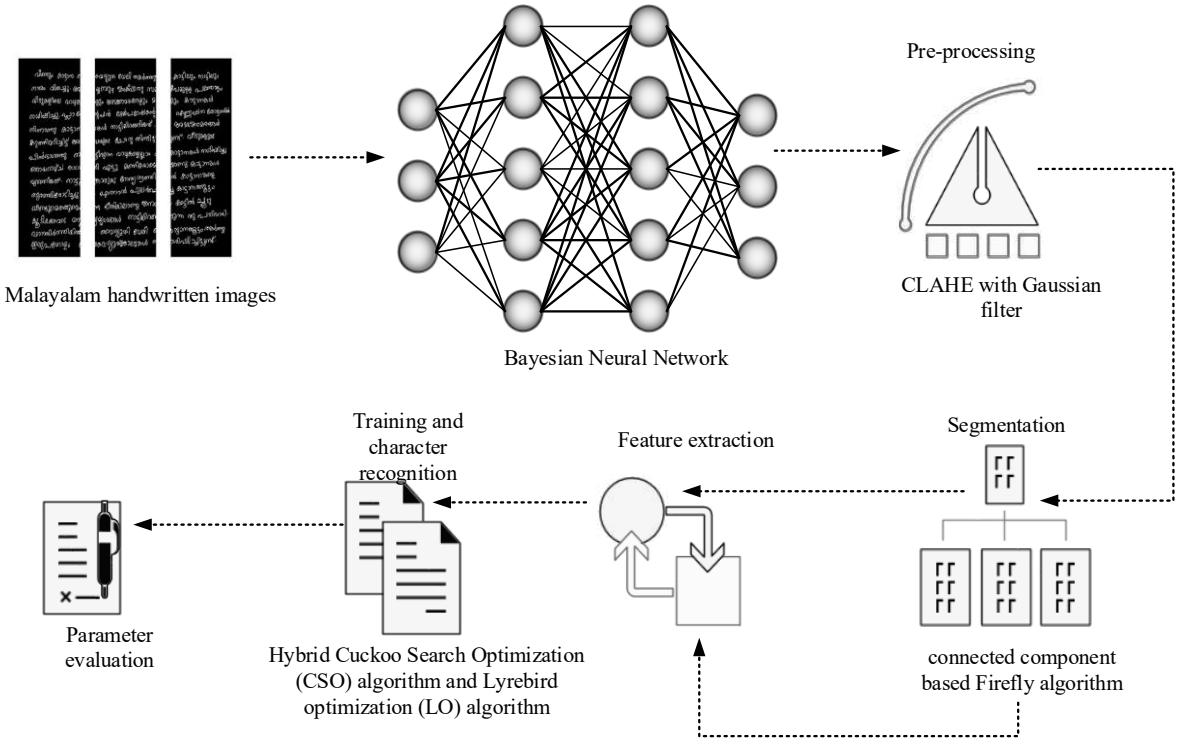


Fig.3 Proposed architecture

Initially the input layer of the BNN has receives the dataset as images which is then proceed under the hidden layers. And finally, results such as classification and prediction will demonstrated in the output layer. Here, Contrast Limited Adaptive Histogram Equalization (CLAHE) [31]with Gaussian filter [32]was utilized improve the local contrast of whole mages. Then Segmentation is function was assists to break the pre-processed image into meaningful regions using Connected Component based Firefly (CCbF) algorithm. Then, most significant features were extracted and finally the model trained based on Hybrid Cuckoo Search Optimization (CSO) [33[algorithm and Lyrebird optimization (LO) [34] algorithm.

4.1 Dataset description

Here, the dataset contains various Malayalam handwritten images for processing the recognition functions. Fig.4 represents sample images and collected by own we have not use any dataset link and database. Moreover, we have attached the collected dataset below,

https://drive.google.com/file/d/16LclqA20G1_REw4l1fgtBSJnlrMDJBFQ/view

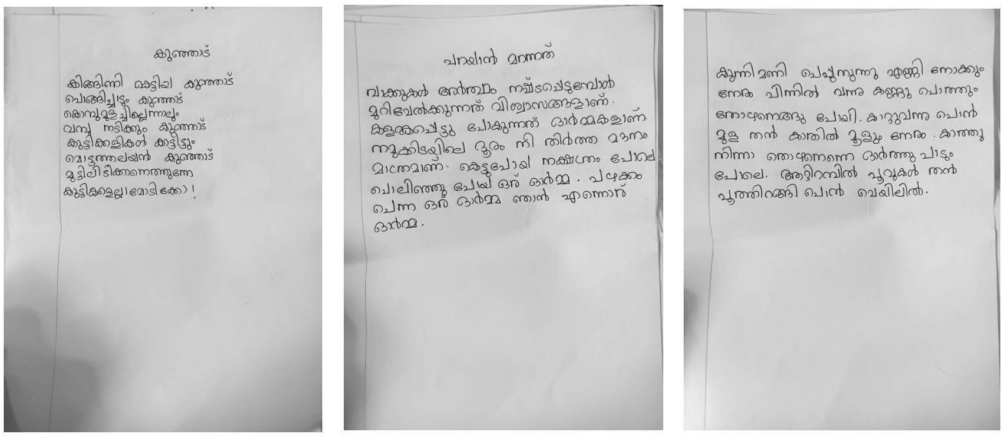


Fig. 4 Original images or sample input images

4.2 Process of proposed BNN-HCSL algorithm

In the Input layer all Malayalam handwritten images are converted into the pixel representation according to the grid values such as . Moreover, the converted pixel has particular grayscale intensity value between 0 to 255. then, this pixel values are termed as input features which are send to the BNN framework. Here, pre-processing layer has done two operation such as CLAHE and gaussian filter function to enhance the contrast of the images and smooths the images. consequently, this stage has prevents the whole images pixel representation as well as small pixel correlations. Segmentation and feature extraction was done on hidden layer of the BNN by applying the CCA with FO. Here, each connected pixels were recognized with respect to the meaningful pixel clusters. Similarly, high level features such as edges, curves, etc has extracted during the pixel grouping interval.

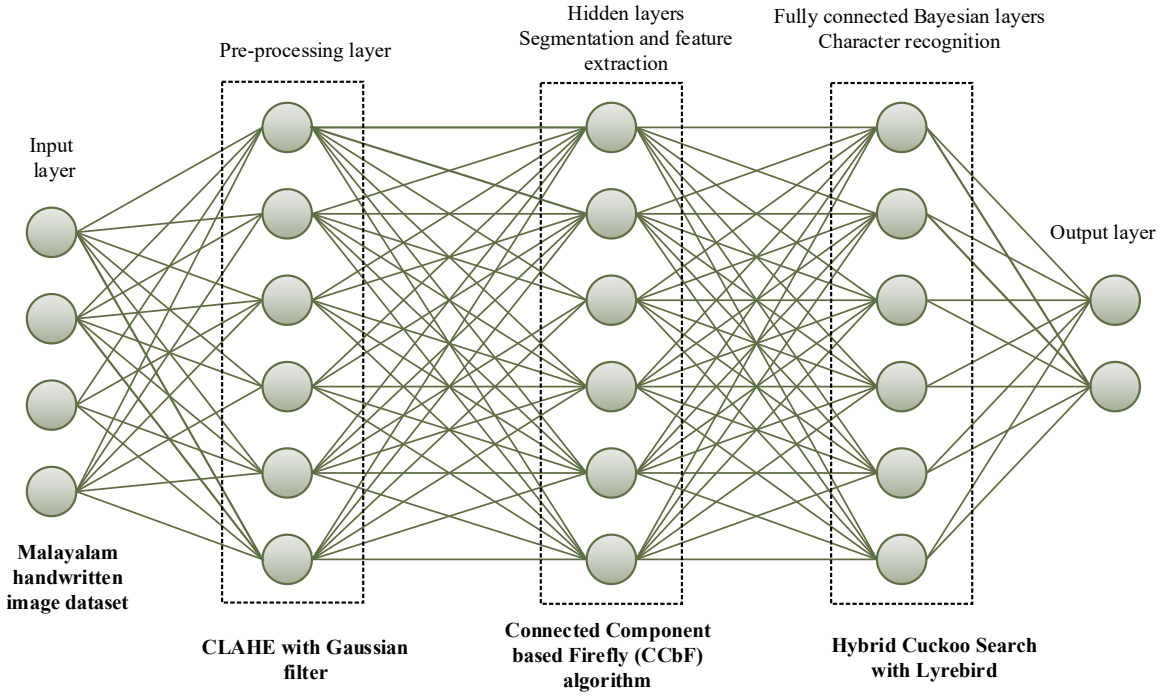


Fig.5 Internal structure of BNN

Instead of Bayesian layers or fully connected layers are effectively mapped the derived pixel from the grouping pixels to analyse the probability distribution of each handwritten characters styes. Furthermore, HCSL algorithm has applied to optimize the character classes in terms of pixel-based features and fine-tuned parameters. Finaly, the output layer has reflected the Malayalam characters corresponds to the neurons with probability distribution.

Table.2. Example for recognized character with highest probability class

Character	**Probability distribution**
അ	0.05
ആ	0.92
ഇ	0.6
ഈ	0.07
ഉ	0.05

4.2.1 Pre-processing using CLAHE with Gaussian filter

In that pre-processing stage CLAHE with gaussian filter was utilised to enhance the Malayalam handwritten images without any undesirable artifacts. Here, CLAHE is one of the adaptive contest enhancement model which is performed based on the histogram modification for improving the traditional CLAHE. Moreover, the proposed pre-processing model was enhanced by applying the image blocks with local contents of the various regions. then, the resultant images were restored after enabling the gaussian filters. CLAHE has serves the image quality, managing the most significant details from the images and achieved higher entropy of the each images. This has two stages such as analysing the optimal parameters and attaining final resultant pre-processed images. Initially, the input images are converted into grayscale format and then histogram distribution using the eqn. (1), (2)

$$I_p(I_m) = RGB \rightarrow G\, I_p(I_m) \qquad 0 \; to \; 255 \tag{1}$$

$$T\left[(I_p(I_m)\right] = A \rightarrow M \;\; h(T).\left[1 - G(T).m_a(T) - m_b\, h(T)\right] \tag{2}$$

Where, $I_p(I_m)$ is denoted as collected input images and the that images were converted into the grayscale format up tom0 to 255 between the black and white values. From the output contain there is no other colours only with gray shades. Moreover, histogram distribution is analysed in terms of threshold computation level which is denoted as $T\left[(I_p(I_m)\right]$, here, the

grayscale images are fed to the histogram equalization which is mentioned as $G(T)$, mean intensity and class intensity of grayscale mages are denoted as $m_a(T) and\ m_b(T)$. In accordance with the histogram distribution valleys and peaks are identified using eqn. (3), (4), here the N-parameter was used to calculates quantification and identification of the valleys and peak numbers.

$$N - Parameter = \frac{\sum V(i)}{N_V} \tag{3}$$

$$(CBD)_T = \begin{cases} \overline{H} = \left(N'_N_p\right) \\ \overline{W} = \left(N'_N_p\right) \end{cases} \tag{4}$$

Where, $V(i)$ is represented as pixel number or frequency of the all identified grayscale image histograms and total number of recognized valleys from the hygrogram distribution images are denoted as N_V. For finding the peaks Context Block Dimension is introduced to ensures all images are in same and acceptable pixel limits. after that natural logarithmic function was combined with the ceiling function to find the peaks with respect to the nearest whole number. Were, N'_N_p is denoted as natural logarithmic variable in terms of pixel height ($\overline{H}$)and weight ($\overline{W}$). Then, the output of the CLAHE was again filtered using the Gaussian filter using eqn. (5),

$$G_F = \sum_{i-1}^{n} (CBD)_T\ I_p(I_m) \tag{5}$$

This Gaussian filter function is the 2D convolution element for smoothening the CLAHE output and managed the overlapped sentence. According to the suggested CLAHE with Gaussian filtering approach, has effectively processing the local features of each image while splitting an image into CLAHE outputs assist to increase the intensity distribution range. In contrast to the traditional CLAHE method, the suggested CLALHE Gaussian filtering offers a locally and adaptively based strategy that sorts the best enhancement parameters to guarantee that every image is effectively improved before applied to form the final image. In this case, a multi-enhancement procedure has enabled to repeatedly improves the quality input image without interrupting noises. By analysing every improved image, this method assists in determining the ideal enhancement parameters. Each image is improved separately using the determined ideal parameters such as ceiling function and natural logarithmic function. This procedure minimizes undesired artifacts while guaranteeing the retention and improvement of

local features. The final image is then created by integrating the improved pre-processed images.

4.2.2 Segmentation and feature extraction using CCbF algorithm

To aggregate pre-processed elements of the same neighbourhood and attributes, the 8-way clustering model was introduced. Moreover, this 8-neighbor connectivity rule is first used to identify all connected pixels. Consequently, this methodology is after applying thresholding, morphological procedures, picture enhancement, and preprocessing. Pixels from the pre-processed image were grouped using this technique which is interconnected sections of darker and brighter binary masks. All connected regions' regional characteristics, including area and pixel distance, were then computed. To find and remove undesirable noises, the Component Connected Analysis (CCA) procedure uses a specific threshold value. The area value, or the total number of pixels in the region, has been empirically selected as the threshold. Every smaller region whose area was below the threshold was eliminated. Then, brighter pixels were combined to create the foreground binary mask, while darker regions were combined to create the background and ROI was extracted using CCA using eqn. (6),

$$n(p) = \left[n \in \alpha : \left| a_n - a_p \right| \right] \tag{6}$$

Where, $n(p)$ is denoted as set of neighbours of image pixel representations, is represented as area under thresholding level and histogram probability.

Moreover FO has utilized based on three rules Regardless of gender, (i) all fireflies will be attracted to one another due to the unisex trait (ii) the more brightness and more attractive the fly, so the fireflies are migrate from one that is less light to one that is brighter. If there are no brighter fireflies, they will migrate at random zone (iii) The objective function of the landscape is directly proportional to brightness. The difference of light intensity and preparation of the attractiveness are the two primary issues with the firefly algorithm. To overcome these issues rules are applied on the CCA based on the image quality intensity. The light intensity of mentioned in eqn. (7),

$$L(i) = L' e^{-\beta r} \tag{7}$$

Where, L' is denoted as light intensity in terms of source, is represented as coefficient parameter of light absorption. Moreover, firefly location is denoted as $L(i)$, $e^{-\beta r}$ is signified as exponential calculation of convergence speed. Then, analyse the attractiveness (δ) using eqn. (8),

$$\delta = \delta' e^{-\beta r} \tag{8}$$

where, the fireflies are mostly relevant to the distance r and light intensity L'. Consequently, the distance among the two fireflies is calculated in terms of ij in eqn. (9),

$$r(ij) = \left\| z_i - z_j \right\| = \sqrt{\sum_{q=1}^{d} \left(z_{i,q} - z_{j,q} \right)^2} \tag{9}$$

Where, $z_{i,q}$ is characterized as position of firefly with respect to the ith position and qth dimension similarly, $z_{j,q}$ is characterized as light intensity with respect to the jth position and qth dimension. Here, the random number series are uniformly assigned with the range of [0,1] and the constant value z. Character segmentation focuses on extracting individual characters from segmented lines. The challenge primarily arises in handling the crescent mark, Chandrakanta, and dependent vowels. Due to these complexities, a single segmentation approach is not sufficient for the Malayalam character set. To maintain character order and enhance accuracy, CCA is applied. CCA in an image plays a key role in automated pattern segmentation by grouping pixels into components according to their connectivity. Once these groups are identified, each pixel is assigned a label and numbered sequentially according to its respective component.

4.2.3 Character recognition using HCSL algorithm

HCSL algorithm has applied to the BNN to train the fully connected layers with character recognition. Initially, define all training parameters such as features, network and loss function. Then, update the fitness function of both optimization such as CS and lyrebird. The way some cuckoo bird species engage in brood parasitism serves as an inspiration for the CS. To improve the chances that their young will live, these birds frequently remove the host's eggs before laying their own in the nests of other bird species. Cuckoos can rely on the host bird's efforts to raise their young instead of spending time and energy on this parasitic activity. Important facets of this conduct consist of:

(i) Selective Nestling: Cuckoo females choose nest locations that increase their eggs and will hatch covertly.

(ii) Egg Imitation: To decrease the rejection of several cuckoo species imitate the look of their host's eggs.

(iii) Chick Domination: In order to remove competition, cuckoo chicks frequently push host eggs or chicks out of the nest. Here, the objective function of character recognition with levy flight population updates using eqn. (10),

$$x(\tau+1)_i = x(\tau)_i + \chi.L(\alpha) \tag{10}$$

Where, $x(\tau+1)_i$ is denoted as new solution, $x(\tau)_i$ is represented as candidate parameter, $L(\alpha)$ is symbolized as stable distribution of levy flight and χ is signified as coordinate function. Then apply the levy distribution function using eqn. (11),

$$L(\alpha) \approx w^{-}\alpha \tag{11}$$

Here, the scaling factors are should recognized under the 0 coefficients and it must be in $1 < \alpha \leq 3$, to computationally exploratory the refine solutions. In addition, locally analyse the levy flight migration approximately using eqn. (12),

$$L = \frac{u'}{|v'|.1/\varepsilon} \tag{12}$$

Where, u' is denoted as $u' \approx N'(0,\phi_{u'}^2)$ and $|v'|$ is represented as $v' \approx N'(0,\phi_{v'}^2)$ and ε is signified as leavy exponent. CS algorithm has verified outstanding effectiveness for addressing the issues including optimization, feature selection because to its essential for simplicity and adaptability. Its resilience to complicated issue sceneries is demonstrated by its capacity to break out from local optima and converge toward global solutions. Moreover, the algorithm's efficiency and application have been greatly increased by the creation of numerous modifications, such as hybrid models, adaptive mechanisms, and domain-specific improvements. Moreover, table.3 represents character mapping label with respect to the Malayalam characters.

Table.3 Label to Character Mapping

Label: 1	◌ഃ	Label: 12	ഓ	Label: 23	ട	Label: 34	ബ	Label: 45	ഷ	Label: 56	ൈ
Label: 2	അ	Label: 13	ഔ	Label: 24	ഠ	Label: 35	ഭ	Label: 46	സ	Label: 57	ൊ
Label: 3	ആ	Label: 14	ക	Label: 25	ഡ	Label: 36	മ	Label: 47	ഹ	Label: 58	ോ
Label: 4	ഇ	Label: 15	ഖ	Label: 26	ണ	Label: 37	യ	Label: 48	◌ാ	Label: 59	ൌ
Label: 5	ഈ	Label: 16	ഗ	Label: 27	ത	Label: 38	ര	Label: 49	◌ി	Label: 60	◌്
Label: 6	ഉ	Label: 17	ഘ	Label: 28	ഥ	Label: 39	റ	Label: 50	◌ീ	Label: 61	◌ൗ

Label: 7	ഉൗ	Label: 18	ങ	Label: 29	ദ	Label: 40	ല	Label: 51	ു	Label: 62	ൺ
Label: 8	എ	Label: 19	ച	Label: 30	ധ	Label: 41	ള	Label: 52	ൂ	Label: 63	ൻ
Label: 9	ഏ	Label: 20	ഛ	Label:31	ന	Label: 42	ഴ	Label: 53	ൃ	Label: 64	ർ
Label: 10	ഐ	Label: 21	ജ'	Label: 32	പ	Label: 43	വ	Label: 54	ൊ'	Label: 65	ൽ
Label: 11	ഒ'	Label:22	ഞ'	Label:33	ഫ'	Label: 44	ശ'	Label: 55	ോ'	Label: 66	ൾ'

Consequently, Lyrebirds make up the population of the suggested Lyrebirds Optimization Algorithm, which is a population-based metaheuristic algorithm. By leveraging its members' search capabilities in the problem-solving area, the LOA can offer appropriate solutions for optimization problems in an iteration-based process. As members of the LOA, each lyrebird chooses the values of the decision variables according to where it is in the problem-solving space. Consequently, each lyrebird may be represented mathematically as a vector, with each component of the vector standing in for a decision variable. A matrix function can be used to mathematically model the population of the algorithm, which is made up of all LOA members. Initially, update the position of Lyrebirds using eqn. (13),

$$Y' = \begin{bmatrix} Y'_1 \\ . \\ Y'_t \\ . \\ Y'_{N'} \end{bmatrix}_{N\times m} = \begin{bmatrix} Y'_{1,1} & \ldots & Y'_{1.d} & \ldots & Y'_{1,m} \\ .. & \ldots & \ldots & \ldots & \ldots \\ Y'_{t.1} & \ldots & Y'_{t.1} & \ldots & Y'_{t,m} \\ \ldots & \ldots & \ldots & .. & \ldots \\ Y'_{N,1} & \ldots & Y'_{N,d} & .. & Y'_{N.m1} \end{bmatrix}_{N\times m} \tag{13}$$

Where, Y' is denoted as population matrix of lyrebird, candidate solution is denoted as $Y'(i)$, dimension with search space variable is denoted as $Y'_{N,d}$. Based on the lyrebird modelling approach for hiding in its immediate safe area, the population member's position in the search space is changed during this LOA phase. The potential of LOA to utilize local search is demonstrated by the lyrebird's ability to manipulate its position by accurately assessing its surroundings and taking tiny steps to get to a good hiding place. Equation (8) is used in LOA design to determine a new position for each LOA member based on the modelling of the lyrebird's movement towards the near-suitable place for coverup. If this new position increases

the value of the objective function as determined by Equation (14), it takes the place of the relevant member's former position.

$$Y_i'(d) = Y_{i,f}' + (1 - 2r_{t,f}).\left[\frac{u'(b)_f - l'(b)_f}{t}\right] \tag{14}$$

$$Y'(t) = \begin{cases} Y_i'(d) & 2r_{t,f} \le F' \\ Y_i' & else \end{cases} \tag{15}$$

$$U \to Y(t) : \begin{cases} phase\,1 & r(p) \le 0.5 \\ phase\,2 & else \end{cases} \tag{16}$$

The procedure described for updating the first lyrebird is also used to update the positions of other lyrebirds in the problem-solving space. At this point, the algorithm's initial iteration is finished after all lyrebirds' positions in the problem-solving space have been updated. Up until this iteration is stored, the best candidate solution is found by comparing the evaluated values for the goal function. The algorithm then moves on to the following iteration, where the procedure for updating lyrebirds in the problem-solving space follows the same steps as for the first iteration and continues until the algorithm's last iteration. The best solution found during the algorithm's iterations is added to the output as a solution to the specified problem once all of the algorithm's iterations have been completed. In this case, the algorithm's implementation is successful. This HCSL optimization algorithm has used to control the local minima, convergence time also enhances the recognition accuracy.

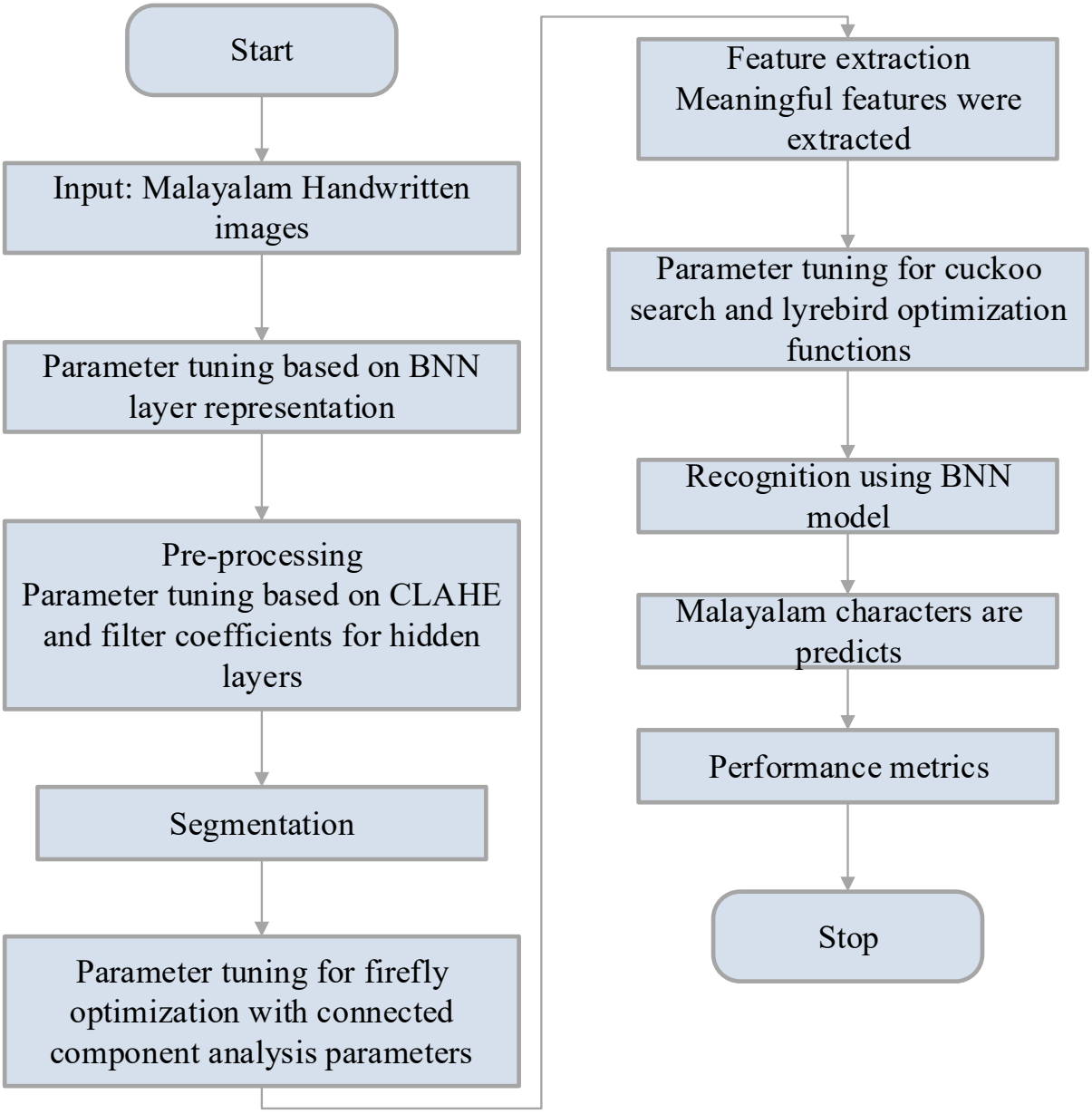


Fig.6 Flowchart for proposed BNN-HSCL algorithm

5. Result and discussion

The developed BNN-HSCL algorithm has implemented on MATLAB platform to recognize the handwritten Malayalam document. Here, The BNN model has effective network and computationally well for performing the multiple operation in single steps. Moreover, CS and LO algorithm has efferently done the character recognition process by applying the fitness function in a hybrid mode from the meaningful extracted data.

5.1 Simulation results

Malayalam handwritten images recognition performance is mainly based on the difference among the pixel intensity of foreground text and background of the paper. Here, the recognition accuracy may me degraded regarding the brightens variation, and contrast also lighting.

Moreover, the CLAHE is used to adjust the local contrast of the images and makes the very closed informal images. This Fig.7 demonstrates brightness and contrast affect readability as well as recognition Malayalam handwritten images.

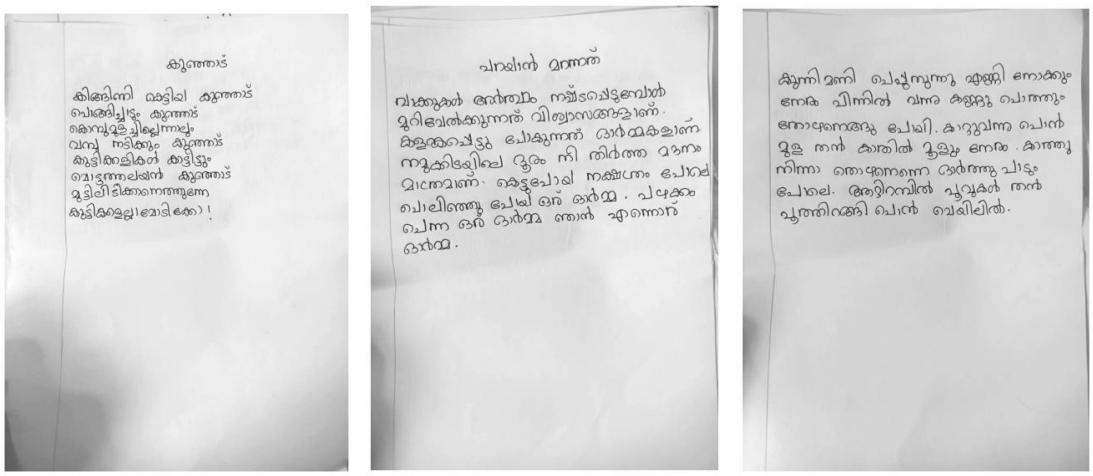


Fig.7 Brightness contrast

This Fig.8 represents binarized image of the Malayalam handwritten images from that collected text samples. The conversion of the grayscale image format into the pixel value representation. Here, foreground text characters are termed as 0 and background paper is denoted as 1. From this stage unwanted barbering noises such as shadows are removed and perfect feature extraction is takes place for more edge detection characters.

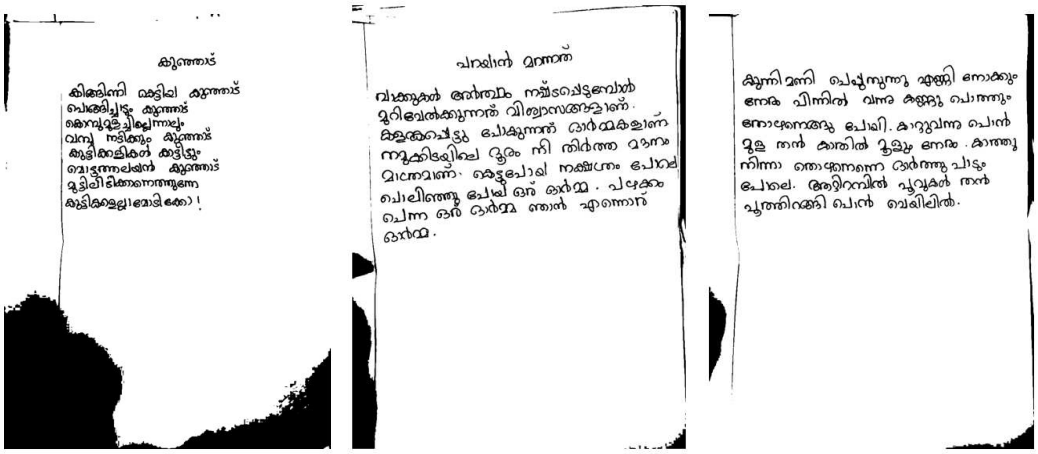


Fig.8 Binarized image

Here, Fig.9 illustrates after applying the histogram equalization function to the Malayalam handwritten mages. In this stage pixel brightness performance are redistributes the all-image intensity value across the darker and brighter regions. Moreover, the blurred images are turned into clearer and simpler to split the character from the particular background. Here, this stage has enhanced the readability and segmentation function for boosting the recognition accuracy.

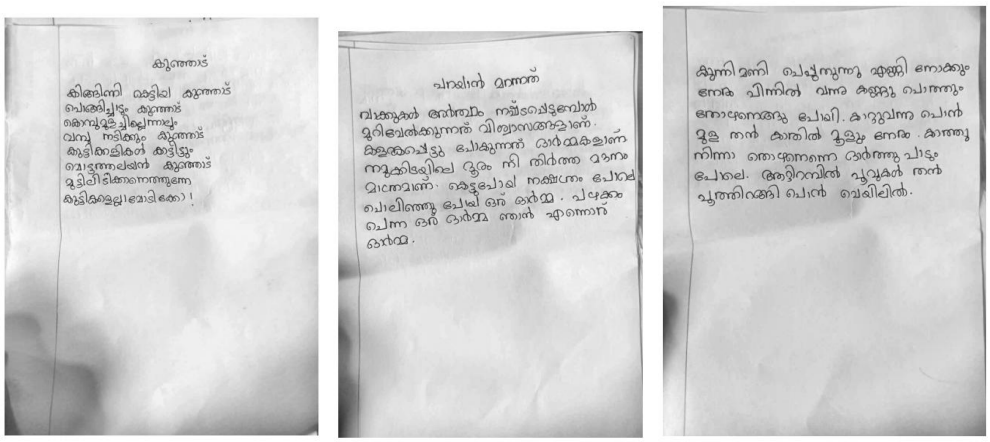


Fig.9 Histogram Equalization

Fig.10 Malayalam handwritten images with applying the gaussian filtered images for reducing the external variation noise presence. in this stage the histogram images are prepared for minimizing the irregularities of the background and text looks very soft and smoothening according to the gaussian filter coefficients.

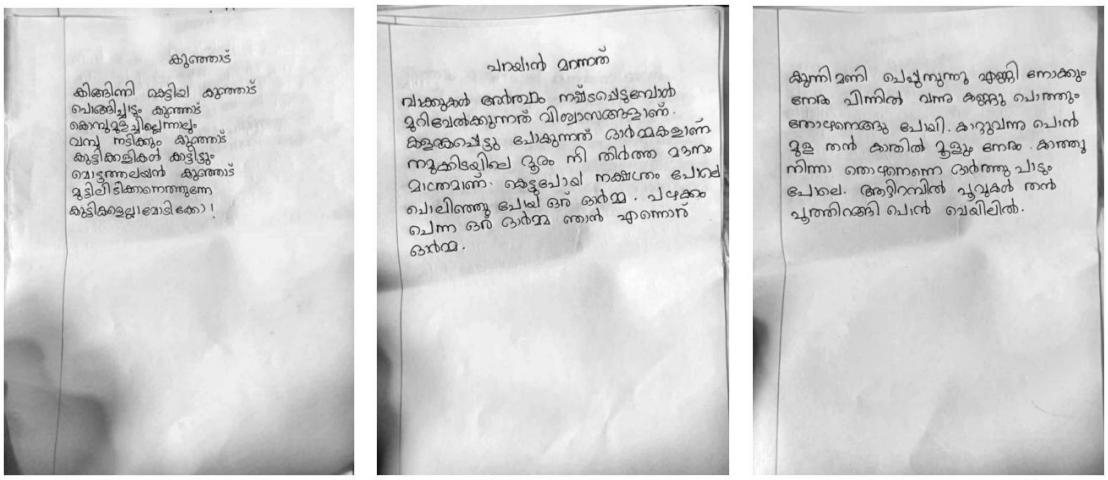


Fig.10 Gaussian filtered image

Fig.11 demonstrates pre-processed output of Malayalam handwritten images before applying the segmentation and character recognition. Here, handwritten images were prepared for the recognition addressing problems more effectively. Consequently, the images text has been improved via CLAHE and gaussian filters with respect to the histogram equalization. Each Malayalam charters are well polished and move to the next process for character segmentation. Segmentation process takes more time since the pre-processing high quality output is delivered to the next process.

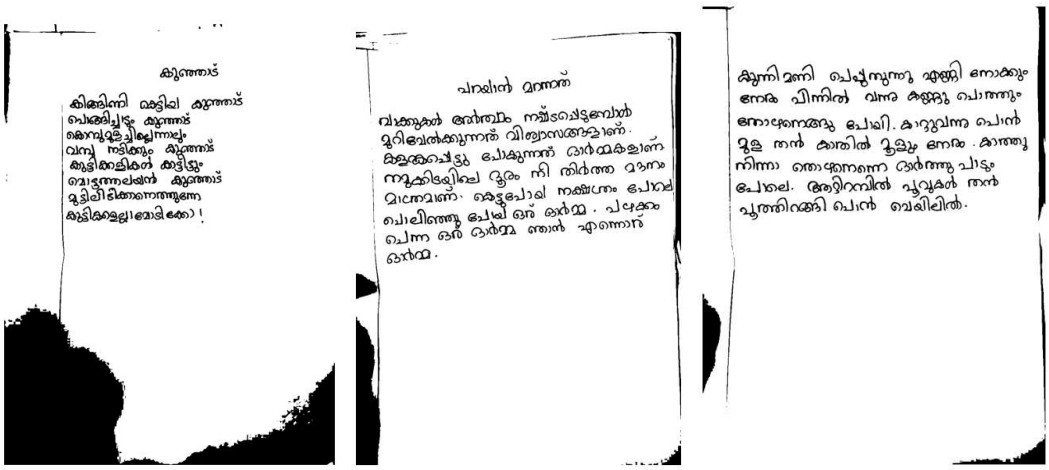


Fig.11 pre-processed image

The segmented lines must then be divided into words. The fundamental idea here is that there is a wider gap between words than there is between characters inside a word. We must compare the estimated distance between the characters with a threshold value in order to divide into words. We have developed a new technique and the procedures involved in firefly optimization to determine the threshold value. To determine the distance between characters, CCA is utilized. The number of black pixels in each column is determined when each line is split vertically into columns. Compare the determined threshold value with the count of consecutive zeroes that was acquired via CCA. The value is selected as the word boundary if it exceeds the threshold value. Figure 12 displays the output that was produced.



Fig.12 Character segmentation

The Connected Component based Firefly (CCbF) algorithm serves as the foundation for character segmentation. However, the Malayalam character set has a crescent mark known as chandrakkala and some dependent vowels, which make it impossible to effectively segment all letters using the vertical projection method alone. Thus, linked component analysis is added

here in addition to the CCBF approach. The characters of a binary image can be found by identifying its related components. However, the letters that are returned might not be in the exact sequence that they appear in a word. Therefore, the Malayalam language cannot be used with either connected component analysis or CCBF alone. We combine the vertical projection method with linked component analysis to improve accuracy while maintaining character order. The total of the pixel values in each image column is shown by the CCBF value. A character boundary is indicated by a vertical projection value of zero since the picture used for character segmentation is a binary image.



Fig.13 sample predection resulst

Moreover, fig.13 sample prediction results of the recognized Malayalam characters from the handwritten images. here, each and every character has different class name with trye label and

prediction level. Based on the predicted class labels each character are isolated from the words and black pixels are grouped under the single characters. Then, the segmented characters are stored into the individual blocks to ensures the clean characters recognition. Finally, the Malayalam handwritten images were converted into the text which is demonstrated in fig. 14.

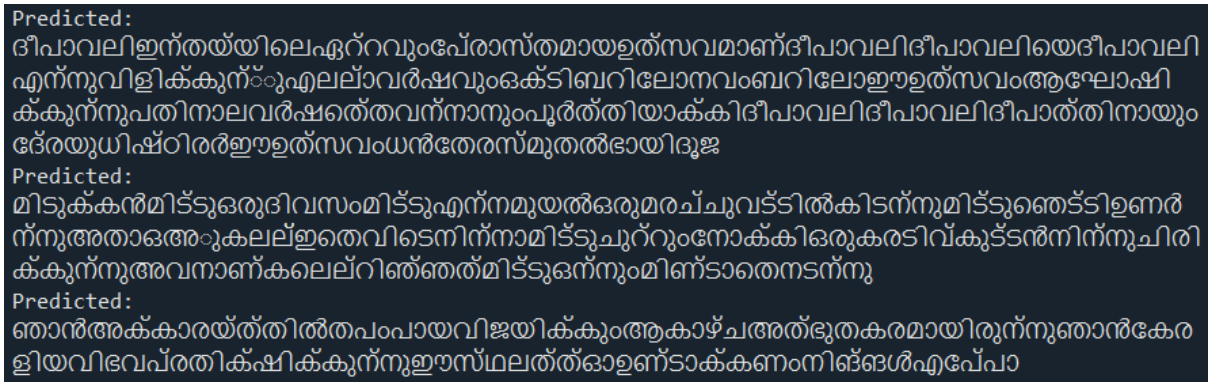


Fig.14 Transcripted images

Moreover, fig. 15 illustrates confusion matrix of the proposed character recognition technique such as BNN-HCSL algorithm.

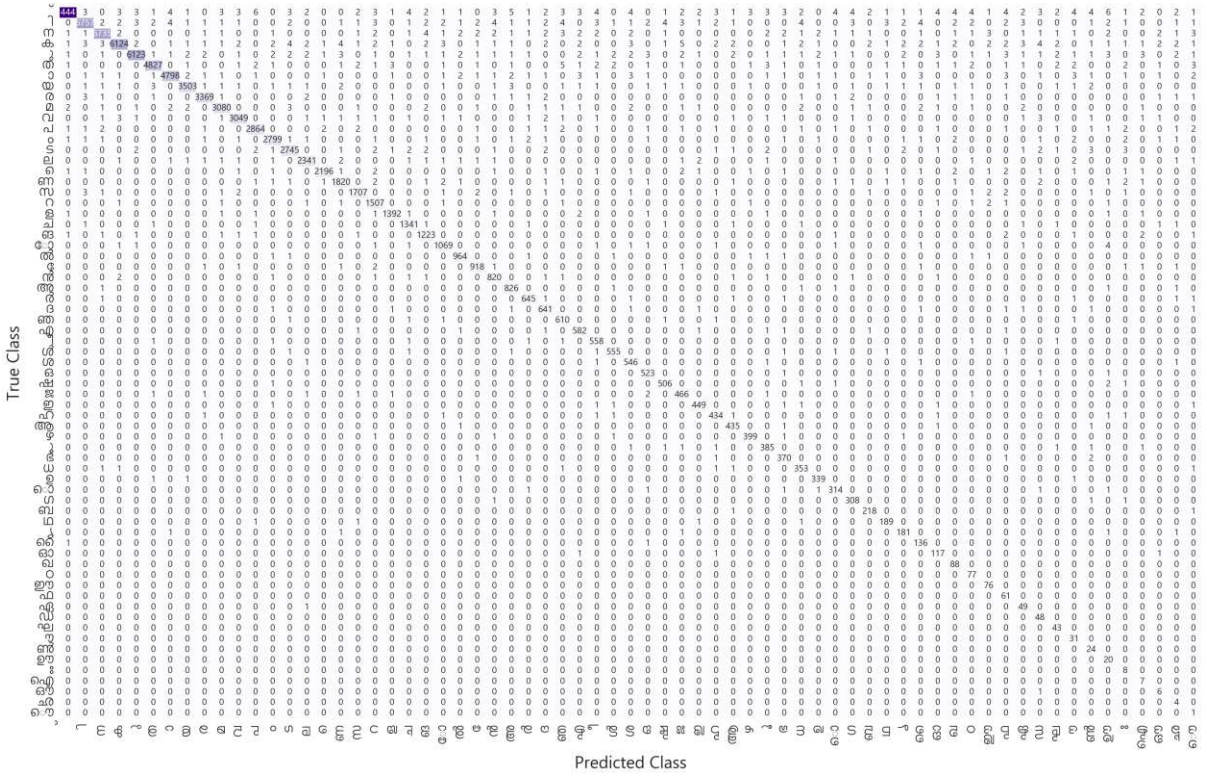


Fig.15 Confusion matrix

5.2 Performance analysis

The attained parameter metrices are validated under the conventional models to illustrates the robustness of the proposed BNN-HSCL replica. Moreover, accuracy, precision, recall, f-

measure and WER are compared and the comparison techniques are Recurrent Neural Network (SARNN) [35], Convolution Neural Network (CNN) [36], Particle Swarm Optimization with Long Short Terms memory network (PSO-LSTM) framework 37 LSTM with Adaptive Federated Learning (LSTM-AFL) network [38] and Optical Character Recognition based Deep Learning (OCRbDL) Model [39].

5.2.1 Accuracy measure

Accuracy is the most significant performance metrices for validating the actual and predicted classes from the handwritten character recognition. Moreover, the correctly predicted values of determined with respect to the inaccurately predicted classes. Consequently, accuracy is analysed in eqn. (17),

$$A_{cc} = \frac{T'(P'')_c + T'(N'')_c}{T'(P'')_c + T'(N'')_c + F'(P'')_c + F'(N'')_c} \quad (17)$$

Where, $T'(P'')_c$ is denoted as correctly predicted true positive classes of Malayalam characters, $T'(N'')_c$ is represented as correctly predicted false positive classes of Malayalam characters, $F'(P'')_c$ is represented as incorrectly predicted true positive classes of Malayalam characters, and $F'(N'')_c$ is represented as incorrectly predicted false positive classes of Malayalam characters.

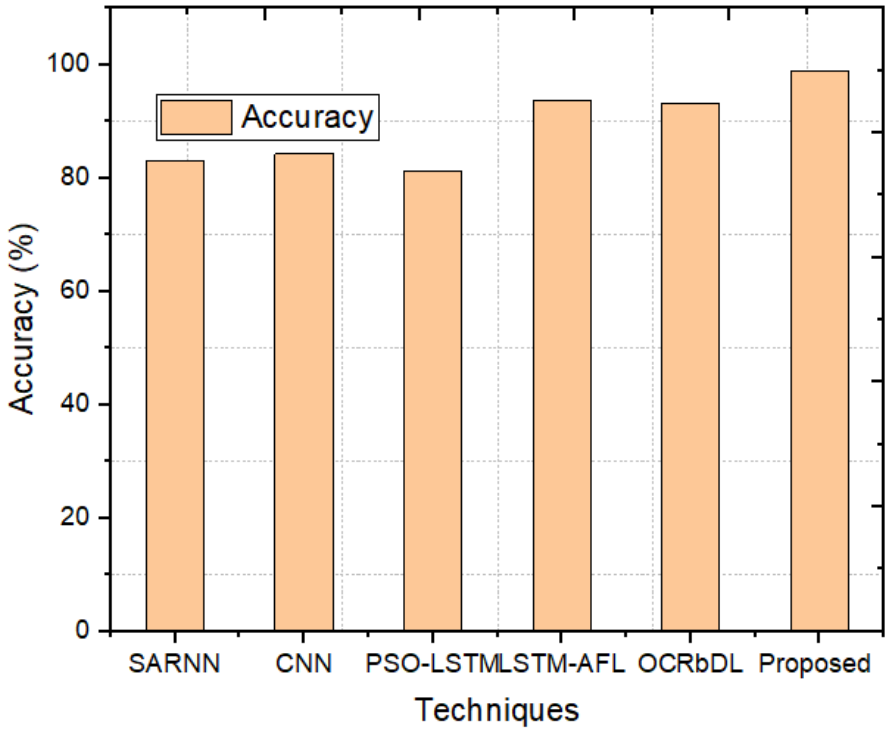


Fig. 16 Analysis of accuracy measure

Accuracy measure of the proposed BNN-HSCL replica has validated under recent techniques

such as SARNN, CNN, PSO-LSTM, LSTM-AFL and OCRbDL, which is illustrated in fig.16. From the comparison SARNN has gained 83.12% of accuracy measure which is lower than the CNN, LSTM-AFL and OCRbDL model and higher than the PSO-LSTM. Then, CNN model has attained 84.35% of accuracy measure which is slightly higher than the PSO-LSTM. Similarly, PSO-LSTM model has achieved 81.24% of accuracy which is lower than the CNN, LSTM-AFL and OCRbDL model. Moreover, LSTM-AFL and OCRbDL model has reached 93.65% and 93.2% accuracy measure. However, the developed BNN-HCSL model has accomplished 98.87% accuracy measure which is higher than all other exiting models. Therefore, the proposed paradigm has well suitable for recognising the characters from particular languages.

5.2.2 Precision measure

Precision is termed as metrics to detect the Malayalam handwritten images system is for finding the each characters. Moreover, trustworthy consistent result is filtered during this parameter training. Moreover, precision is analysed in eqn. (18),

$$P_n = \frac{T'(P'')_c}{T'(P'')_c + F'(P'')_c} \quad (18)$$

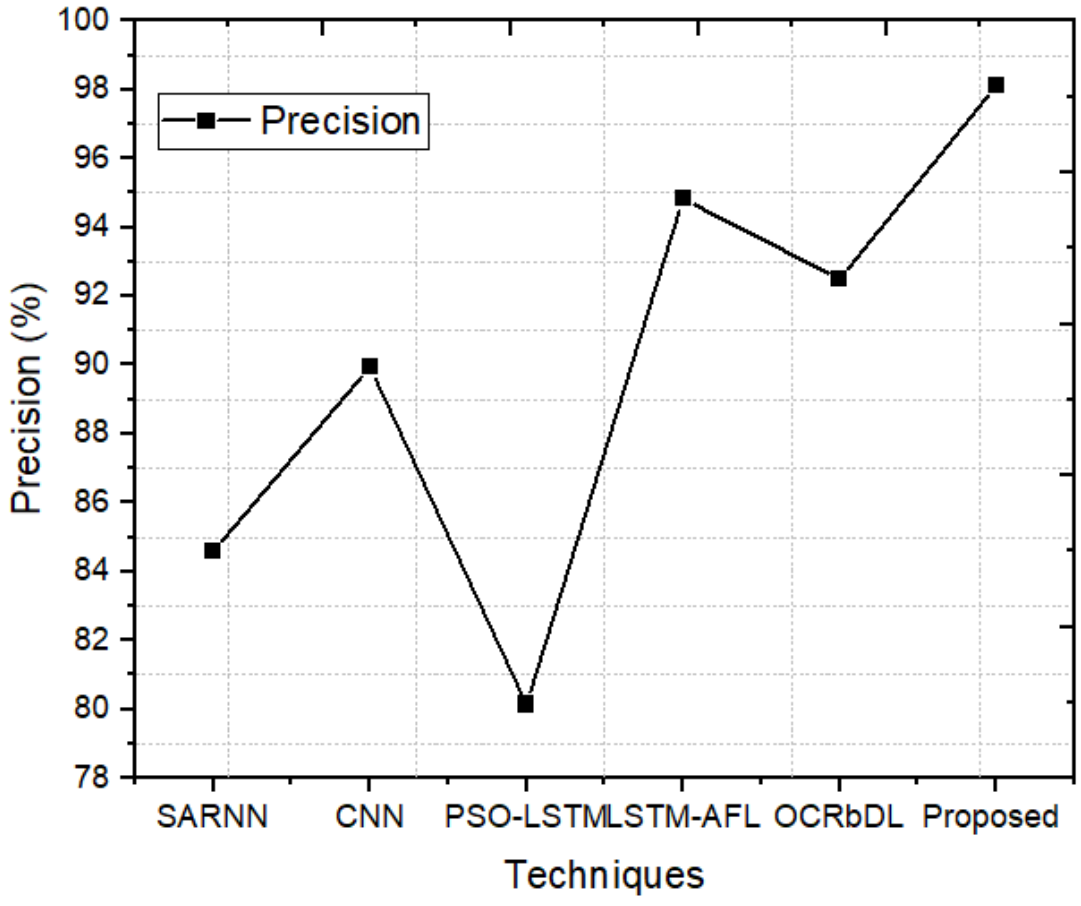


Fig. 17 Analysis of precision measure

Precision measure of the proposed BNN-HSCL replica has validated under recent techniques such as SARNN, CNN, PSO-LSTM, LSTM-AFL and OCRbDL, which is illustrated in fig.17.From the comparison SARNN has gained 84.6% of precision measure which is lower than the CNN, LSTM-AFL and OCRbDL model and higher than the PSO-LSTM. Then, CNN model has attained 89.94% of precision measure which is slightly lower than the PSO-AFL and OCRbDL. Similarly, PSO-LSTM model has achieved 80.15% of precision which is lower than the CNN, LSTM-AFL and OCRbDL model. Moreover, LSTM-AFL and OCRbDL model has reached 94.83% and 92.5% precision measure. However, the developed BNN-HCSL model has accomplished 98.12% precision measure which is higher than all other exiting models. Therefore, the proposed paradigm has well suitable for recognising the characters from particular languages.

5.2.3 Recall measure

Recall is defined as the ability to determine the all positive classes which has represented by accurately delivered Malayalam characters from the handwritten images. Also, recall is calculated by applying the total true positive predicted classes by the false positive classes.

$$R_l = \frac{T'(P'')_c}{T'(P'')_c + F'(N'')_c} \quad (19)$$

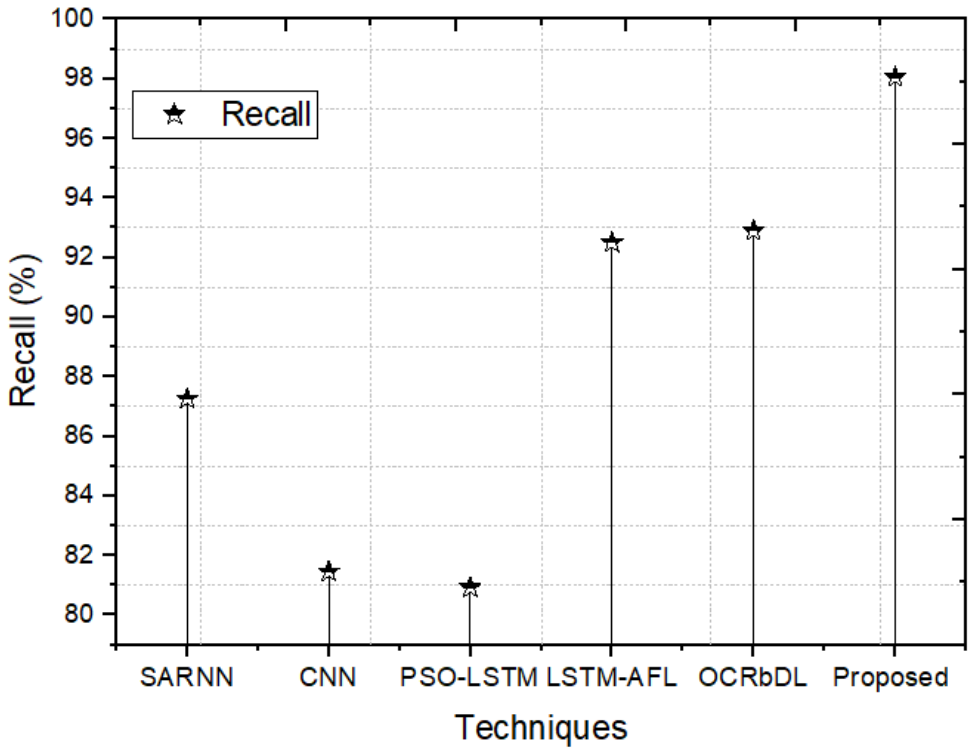


Fig. 18 Analysis of recall measure

Recall measure of the proposed BNN-HSCL replica has validated under recent techniques such as SARNN, CNN, PSO-LSTM, LSTM-AFL and OCRbDL, which is illustrated in fig.18.From the comparison SARNN has gained 87.25% of recall measure which is lower than the LSTM-AFL and OCRbDL model and higher than the CNN and PSO-LSTM. Then, CNN model has attained 81.45% of recall measure which is slightly lower than the PSO-AFL models. Similarly, PSO-LSTM model has achieved 92.5% of recall measure which is lower than the OCRbDL model. Moreover, LSTM-AFL and OCRbDL model has reached 92.5% and 92.9% recall measure. However, the developed BNN-HCSL model has accomplished 98.05% recall measure which is higher than all other exiting models. Therefore, the proposed paradigm has well suitable for recognising the characters from particular languages.

5.2.4 F-measure analysis

F-measure is analysed based on the results of accuracy and precision classification together to perform the effective F1 score results. Here, the higher percentage of F-measure indicates better recognition rates under the training parameters. F-measure is calculated in eqn. (20),

$$F_m = 2 \times \frac{P_n \times R_l}{P_n + R_l} \tag{20}$$

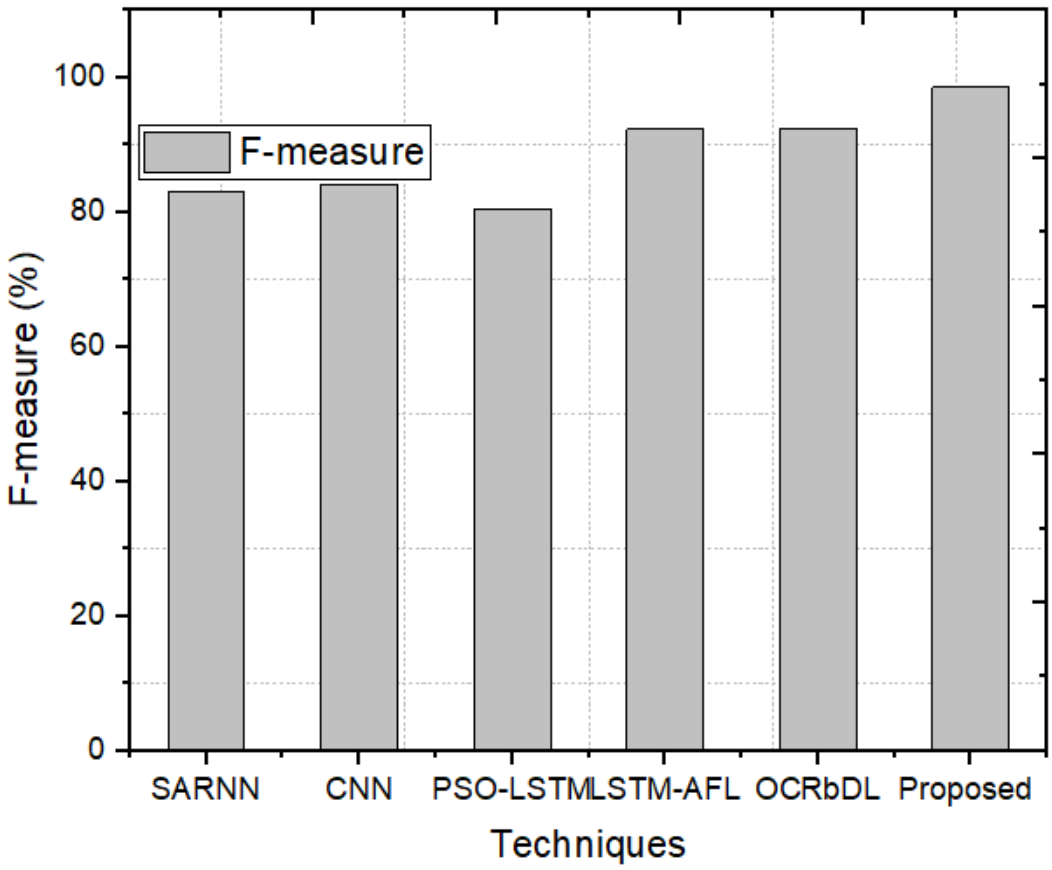


Fig. 19 Analysis of F-measure

5.2.5 Word Error Rate (WER)

WER is one of the most common performance metrics to analyse the OCR systems and find the error during the testing time. Moreover, WER is calculated using eqn. (21),

$$WER = \frac{s' + d' + i'}{n} \tag{21}$$

Where, s' is denoted as total number of substitutions which is replaced by another character or word, d' is represented as total number of deletions which is missing from the hypothesis, i' is signified as insertions which is adding extra character from the sentence and finally n is symbolised as total number words present in the handwritten document.

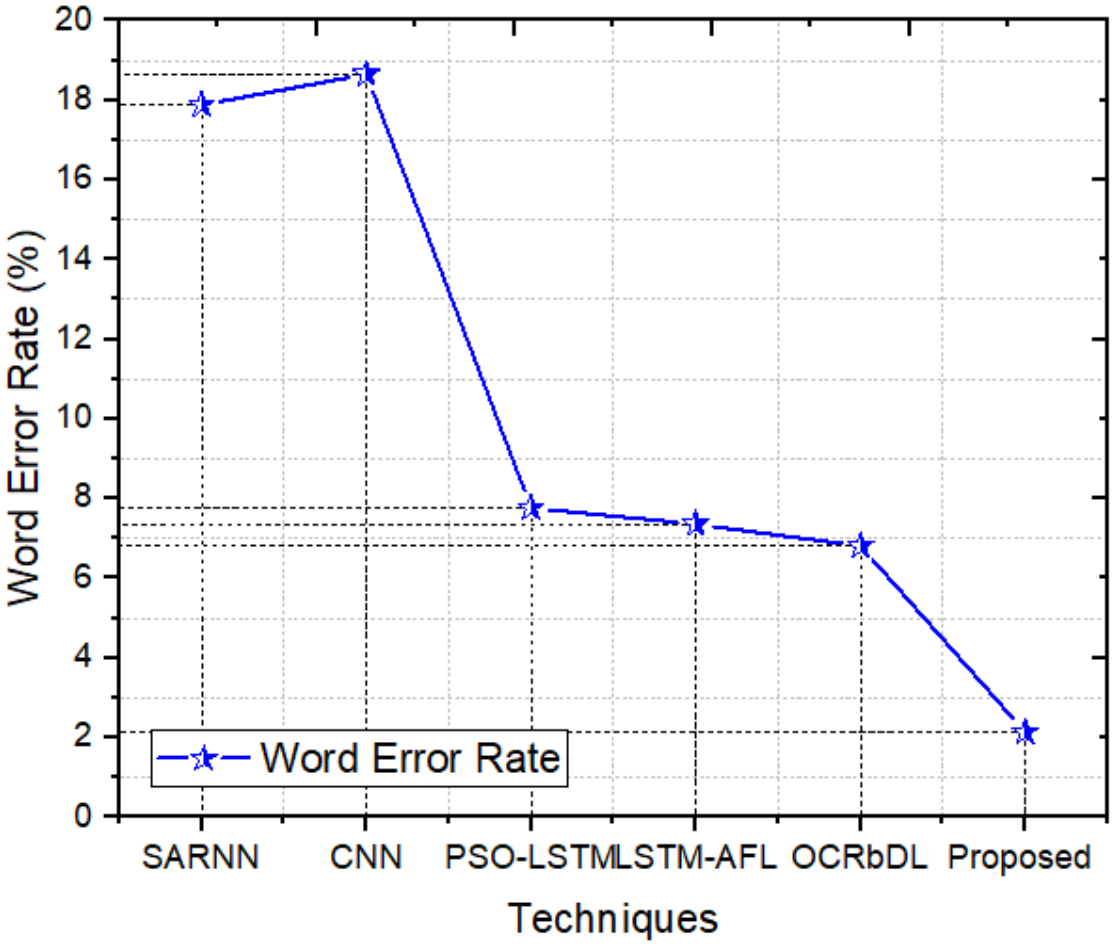


Fig. 20 Analysis of WER

WER of the proposed BNN-HSCL replica has validated under recent techniques such as SARNN, CNN, PSO-LSTM, LSTM-AFL and OCRbDL, which is illustrated in fig.20.From the comparison SARNN has gained 17.88% of WER which is lower than the LSTM-AFL and OCRbDL model and higher than the CNN and PSO-LSTM. Then, CNN model has attained 18.65% of WER which is slightly lower than the PSO-AFL models. Similarly, PSO-LSTM model has achieved 7.76% of WER which is lower than the OCRbDL model. Moreover,

LSTM-AFL and OCRbDL model has reached 7.35 and 6.8% WER. However, the developed BNN-HCSL model has accomplished 2.13% F-measure which is higher than all other exiting models. Therefore, the proposed paradigm has well suitable for recognising the characters from particular languages. Table.4 represents overall comparative analysis.

Table.4 Overall Comparative analysis

Techniques						
Parameters	**SARNN**	**CNN**	**PSO-LSTM**	**LSTM-AFL**	**OCRbDL**	**Proposed BNN-HCSL**
Accuracy	83.12	84.35	81.24	93.65	93.2	**98.87**
Precision	84.6	89.94	80.15	94.83	92.5	**98.12**
Recall	87.25	81.45	80.92	92.5	92.9	**98.05**
F-measure	82.92	84.19	80.53	92.4	92.4	**98.58**
WER	17.88	18.65	7.76	7.35	6.8	**2.13**

6. Conclusion

This paper has proposed an advanced intelligent BNN-HCSL optimization-based ML paradigm for the recognising the Malayalam handwritten image characters. Moreover, the BNN-HCSL algorithm has consists various stages for processing the better outcomes such as preprocessing, segmentation, feature extraction, recognition and parameter optimization. The main aim of this developed BNN-HCSL replica is to functioned a hybrid CSL algorithm for the parameter optimization of the BNN models. Moreover, the use of hybrid CSL model helps to significantly improves the character recognition process. In order to demonstrated the enhanced Malayalam handwritten recognition performance of the developed BNN-HCSL replica, general sets of simulation were conducted on MATLAB and the experimental outcomes highlighted the improved recognition performance with a maximal accuracy, average, precision and recall and minimal WER of 98.87%, 98.12%, 98.05% and 2.13% respectively. In future, the proposed MOMFO-DL model will extended to the development of hybridized segmentation techniques and feature selection approaches.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable
Conflicts of interest Statement: Not applicable
Consent to participate: Not applicable
Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.
Code availability: Not applicable

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