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***Research paper***

# Optimized Type - 3 Fuzzy Logic for Robust Learning Algorithm in OCR Recognition

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## Abstract

Optimized Type-3 Fuzzy logic system integrated with robust learning algorithm and enhanced with OCR performances. This approach is specifically within the context of educational applications. OCR played an important role in converting printed educational materials into digital formats. The reason for selecting fuzzy logic in the education sector is not only learning for the decision-making process. Fuzzy logic is a more realistic and flexible evaluation. Results as more consistent, objectives. Type-1 fuzzy logic systems have single-valued membership functions, they only handle basic-level operations. Type-2 fuzzy logic is computationally more complex with requires larger resources to process in educational applications. To overcome this issue Optimized Type-3 Fuzzy logic combined the type-1 and type-2 fuzzy logic systems with the terms to improve the adaptability and performance. Introducing the optimized Type-3 fuzzy logic algorithm used PSO noted as PSO-OT3FL-RLA, helps to improve the accurateness and strength of the OCR system. This system also incorporates uncertainty in the recognition process and ensures adaptable recognition outcomes. The proposed model is an advanced learning algorithm integrated with fuzzy logic that effectively handles noisy input data. PSO technique ensures efficient exploration and maintains the balance between the quality of the result and computational efficiency. Utilize the proposed approach performed through the traditional OCR methods in terms of accuracy and computational error rate. After evaluating the overall performance of the proposed model, we provide a result of 94.67%. It provides a promising solution for OCR-based applications in educational sectors.

***Keywords***: *OCR; Type-3 Fuzzy Logic; Robust Learning Algorithm; Educational System; Recognition Accuracy; Optimization and Noise Handling.*

## 1. Introduction

Fuzzy logic is the computational method used to deal with fixed and exact values, which is the traditional binary logic used to deal with true and false values. Type-3 Fuzzy Logic also known as interval type-3 fuzzy logic, is the extension method of conventional types of fuzzy logic systems [2]. It also handles a higher level of uncertainty with more robustness in various situations. Type 3 fuzzy logic should play an important role in robust learning algorithms in OCR recognition. This type of system is more effective in handling uncertain present data such as noise, and unclear handwriting. It is useful for making OCR recognition more robust and adaptable to different types of inputs making as a promising tool for improved OCR performances, and dealing with noisy, uncertain. Its more flexible approach to handling uncertainty also enhanced the ability to learn as complex leading to analysis the better results.
OCR system is the process, of covert scanned images to machine-readable text, this time faced various challenges due to Quality, noise, and distortions [6]. To improve accuracy, integrate the Type-3 Fuzzy logic and PSO emerged to provide the possible solutions [20]. To combine this type of flexibility, the OCR system must be robust and adaptable to various types of input types. Type-3 Fuzzy logic handles the higher level of uncertainty, useful for complex solutions. This proposed model provides the ability to analyze character recognition. PSO (Particle Swarm Optimization) is the technique that helps to enhance performance and accuracy. Combining the Type-3 fuzzy logic and PSO, improved the robustness by fine-tuning parameters [21]. The benefits of this proposed model as Robustness of character recognition, Improved accuracy in noisy data, and optimizing the performances. In the education sector, to implement an automated grading system, language translation and analysis, language translation and analysis [4].
Key Findings

- Optimized Type-3 fuzzy logic greatly improves OCR systems' ability to identify characters from distorted or noisy images.
- Compared to Type-1 and Type-2 fuzzy logic systems, Type-3 fuzzy logic's capacity to manage greater levels of uncertainty is one of its most notable characteristics.

This research report is followed by various chapters, chapter 1 describes introduction of the research topic with the education sector. Chapter II describes fuzzy logic in the OCR system and optimized type-3 fuzzy logic for OCR. Chapter III Primilieries explained about common steps for character recognitions. Chapter IV describes the proposed architecture of PSO-OT3FLRLA and contains various steps such as Image Acquisition, segmentation, pre-processing, feature extraction, and feature selection". Classification using the proposed model covers type 3 fuzzy logic, PSO, data flow diagram, and proposed algorithm. Chapter V describes dataset details, Analysis metrics, and Performance evaluation. Chapter VI summarized the information related to the research topic. Chapter VII shows what references are covered by this research paper.

## 2. Related work

### 2.1. Fuzzy logic in OCR system

Fuzzy logic is the subfield of artificial Intelligence, enabling the management of imprecision and uncertainty of data. According to the author describes that it is classical logic, which is used by binary values such as true or false [10]. This logic is used by degrees of truth to make it possible to represent the concepts of unclear. By using degrees of truth followed by true or false classifications [35]. Fuzzy logic helps OCR handle uncertainties of image data, Specifically, it deals with noise or poorly defined characters. These mimic human reasoning in interpreting ambiguous visual information, essentially improving the system's ability to recognize characters that might not exactly match a standard template due to factors like font variations, image quality, or slight distortions [15]. This type of algorithm is used by fuzzy logic to analyze and identify the patterns. It is the mathematical approach to deal with imprecision and uncertainty [8].

### 2.2. Optimized type-3 fuzzy logic for OCR

Optimized Type-3 Fuzzy logic is the new study and interacts with other fields. It's achieved by the same level of result related to Type-1 and Type-2 fuzzy logic with in terms of widespread applications. Modeling uncertainty and imprecision is a complex system done accurately and adopted with type 3 fuzzy logic, which is the extension of standard fuzzy logic. The author says. It is the ability to handle the fuzzy set with time and space varies from the Type -1 and Type 2. Which is suitable for dynamic systems, T3FL is used for the harmony search as dynamic, Optimized Type-3 fuzzy logic for Optical Character Recognition, it is the secure method for finding accuracy depending upon the OCR task along with the flexibility of fuzzy logic. Type-3 Fuzzy logic system is an extension of Type-2 fuzzy logic system [33]. It enables handling the data noise, uncertainty, and imprecision [36]. Character recognition in OCR from scanned documents or images can be difficult because of environmental factors like "dim lighting, handwriting variations, noise, and distortions". These doubts can be healthier managed by fuzzy logic systems, especially Type-3, then by conventional techniques. "Uncertainty and noise handling, feature extraction, rule-based decision making, and system optimization" are further details of how Type-3 fuzzy logic was optimized for OCR. In the presence of uncertainty and noisy data, Optimized Type-3 Fuzzy Logic can be a potent tool for enhancing OCR systems. Particularly in more difficult OCR tasks like handwritten text recognition and degraded document scanning, it provides benefits in terms of strength and adaptability by integrating fuzzy rules and managing imprecision efficiently [16]. The fuzzy logic system must be properly trained and optimized to meet the unique OCR challenges for the implementation to be successful [22].

## 3. Primilieries

Character Recognition Steps

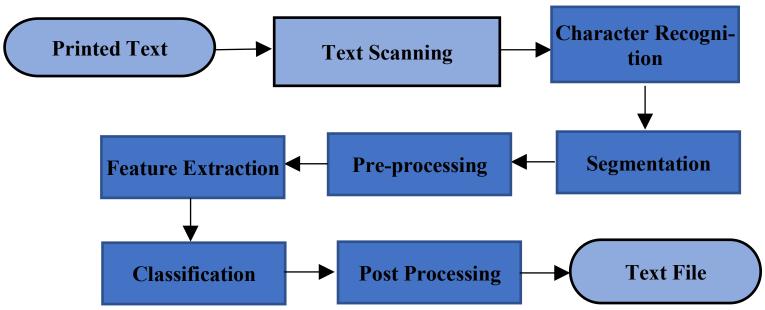


**Fig. 1:** Character Recognition Steps.

OCR System contains the six stages such as "image acquisition, segmentation, preprocessing, feature extraction, post-processing, and classification". Two major factors are affected by the OCR recognitions, which contain features from the word images and robust classification algorithms. The selection table contains the set of structures, that is essential to the OCR system design. The operation of this system design contains the important features connected through the feature vector. The OCR classification technique is classified into three categories such as heuristic, template matching, and learning-based methods. These algorithms are suitable for fitting consequences. Here used a generalized training data set [23]. Character recognition Steps shown in Fig. 1.

The process of selecting features involves obtaining input at the majority of the predictive level. A variety of methods are employed to identify redundant features or accuracy within the predictive level. The feature selection method used by the generic algorithm is the most advanced and essential one. It is the positive method to function up to the biological evolutions. Applying the generic algorithm in feature selection, it's had more features to optimize the performance of the predictive model [5]. Here describe the many advantages of this algorithm over the optimized one. It also deals with complex problems and parallelism. It's used to check whether the function is stationary or non-stationary, linear or non-linear, or random noise. In the implementation stage Optimized algorithm does not require any kinds of structures [26]. A classical optimization model should be used as some information. PSO-OT3FLRLA was well established and standard optimized algorithm with recognition applications. PSO is used to optimize the selection of features, that represent the characters [25]. PSO is used to optimize the fuzzy rules, membership functions, and decision-making parameters. According to that fuzzy algorithm was powerful and not very sensitive to changing the environment or gone rules. Here analysis of some issues related to obtaining a good sentence, OCR overcomes these natures of characters followed by recognition rate and styles [27].

# 4. Proposed model

## 4.1. Proposed architecture of PSO-OT3 FLRLA

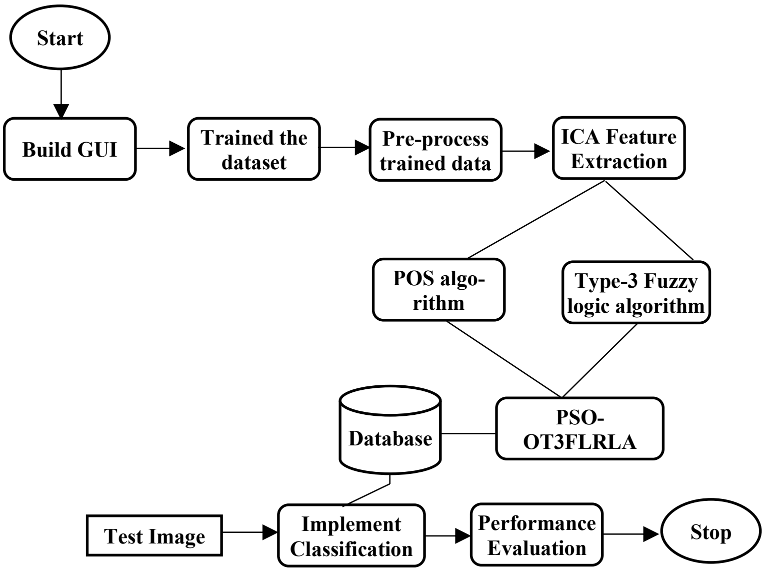


**Fig. 2:** Proposed Architecture of PSO-OT3FLRLA.

### 4.1.1. Image acquisition

The proposed model is used by a printed database, which has a high-quality resolution, Font size, and text images. Two types of data sets are used as IAM and IIIT, IAT expanded as a writing Database, which contains the English text, and it is used for training and evaluating the Handwriting recognition system. IIIT dataset combines images with words related to real-world settings. These types of datasets have different sizes, orientations, and noise. Proposed Architecture of PSO-OT3FLRLA shown in Fig. 2.

### 4.1.2. Segmentation

Segmentation is the major basis for detecting errors, the proposed model should avoid these steps and use the pre-segmented images. These types of images come from the IIIT database are have lines of words. Segmentation procedure implemented manually. A line segmentation algorithm is used to extract each line text from the image for further processing [7]. Here faced with some challenges as overlapping boundaries, border lines, touching lines, and touching characters and words within the line Depends upon the input digital image text.

### 4.1.3. Preprocessing

The primary goal is to make every image associated with the OCR model visible. To prepare the feature extraction, this model includes the five fundamental operations for each sample size and processing phase. These processes are primarily concerned with converting the image to binary format and greyscale. Use an appropriate filter to eliminate noise from all photos. Use morphologic open and close operations to eliminate any small objects. To turn the matching pictures around. The scale issue caused by different sizes and scales can be resolved by resizing the image after the specified dimensions [38].

### 4.1.4. Feature extraction

The primary objective of this section is to optimize the recognition rate while storing the fewest features possible in the feature vector. Extracting features from word images and achieving a high degree of samples within the same class which contains high degrees of variation among the other classes are the fundamental concepts of the stage. Feature extraction is followed by high differentiation rates to obtain second-order statistics [9].

### 4.1.5. Feature selection

In order to create the predictive model with the highest accuracy, feature selection focuses on identifying the subset of the original feature that contains the dataset. The induction algorithms use a feature selection process that contributes to the potential accuracy. The feature selection method used in the suggested model should incorporate the methodical process taken into account for each of the various classes [11].

## 4.2. Classification using PSO-OT3FLRLA

Type 3 Fuzzy Logic

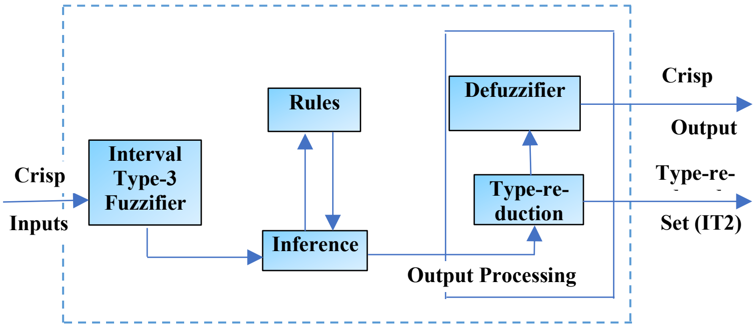


**Fig. 3:** Type 3 Fuzzy Logic Processing Stage.

The term "classification using Type 3 fuzzy logic in OCR character recognition" refers to a technique in which characters extracted from an image during Optical Character Recognition (OCR) are classified using fuzzy logic, specifically the Type 3 variant. Fig. 3 contains the Interval types fuzzifier and output processing unit [39]. In a processing stage type 3 fuzzy logic system received the input system as membership function. The fuzzification unit helps to convert the crisp input values into the fuzzy set. The system has fuzzy rules, which apply the set of fuzzy inference rules to fuzzy input and also interpret the relationship between the different types of fuzzy input. The interference mechanism is the engine process through fuzzified input, fuzzy rules produce the fuzzy output values. Type-3 fuzzy system output encapsulated through all possible stages of output accounts of output membership functions. The defuzzification unit should convert aggregated output to crisp values.
This permits the system to handle uncertainties and uncertainties in the character shapes and is especially helpful for identifying handwritten or poorly scanned text where pixel variations may occur. This type of fuzzy logic is more sophisticated than Type 1 or Type 2 fuzzy logic, handling higher levels of uncertainty and allowing for complex membership functions. The use of Type 3 fuzzy logic in OCR has several advantages, including increased accuracy, noise resistance, and style adaptability [12]. T3FL's versatility in handling fuzzy sets with time- and space-varying membership functions makes it particularly well-suited for various scientific and engineering applications. Data analysis, recommendation systems, information filtering, and intelligent control systems are just a few of the current uses and effects of T3FL. The application of T3FL in the field of control is a crucial area for our work. T3FL is used to create controllers that can change their parameters in response to real-time information and changing environmental conditions. This enables more resilient and adaptable control when systems are unpredictable, nonlinear, or disposed to sudden changes [13]. T3FL is being investigated in domains like traffic control systems, industrial automation, and robotics to improve the responsiveness and flexibility of systems to shifting and variable circumstances [14].

$$x1 = x2$$

$$xn = f(x) + \Delta f(x) + \emptyset(u) \tag{1}$$

From equation (1) Where $x = [x1, x2, \dots \dots . xn]Tx = x1, x2, \dots \dots xnT, f_1(x)f_1x$ is the unknown function, $\Delta f(x)\ \Delta fx$ is the dynamic function, u is the controller and $\emptyset(u)\emptyset u$ represents as a faulty actuator.
Inputs are noted as r-th, T3FLS are $xi, i = 1, \dots . . ni = 1, \dots \dots \dots n$.
The upper and lower memberships.

$\theta_i^{\sim j}$ at slice $u_s = q_{-k}$ and $u_s = q_{\bar{k}}$

$$\rho^{-}\theta_i^{\sim j}|_{us=q^{-k}} = \begin{cases} 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) - qk \text{ if}_1 c_{\theta_i^{\sim j}} - d_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} \\ 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) - qk \text{ if}_1 c_{\theta_i^{\sim j}} - d_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} \\ 0 \text{ if} x_i > c_{\theta_i^{\sim j}} + d_{c_{\theta_i^{\sim j}}}^{-} \text{or } x_i \le c_{\theta_i^{\sim j}} - d_{-\theta_i} \end{cases}$$

$$\rho^{-}\theta_i^{\sim j}|_{us=q^{-k}} = \begin{cases} 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) q^k \text{if}_1\ c_{\theta_i^{\sim j}} - d'_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} \\ 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) q^k \text{ if}_1\ c_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} + c_{\theta_i^{\sim j}} \\ 0 \text{ if} x_i > c_{\theta_i^{\sim j}} + d_{c_{\theta_i^{\sim j}}}^{-} \text{or } x_i \le c_{\theta_i^{\sim j}} - d_{-\theta_i} \end{cases}$$

$$\rho^{-}\theta_i^{\sim j}|_{us=q^{-k}} = \begin{cases} 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) \frac{1}{qk} \text{ if} c_{\theta_i^{\sim j}} - d_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} \\ 1 - \left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_i^{\sim j}}\right) \frac{1}{qk} \text{ if} c_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} + d_{c_{\theta_i^{\sim j}}}^{-} \\ 0 \text{ if} x_i > c_{\theta_i^{\sim j}} + d_{c_{\theta_i^{\sim j}}}^{-} \text{or } x_i \le c_{\theta_i^{\sim j}} - d_{-\theta_i} \end{cases}$$

$$\rho^{-}\theta_i^{\sim j}|_{us=q_{-k}} = \begin{cases} 1-\left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_{i\ -}^{\sim j}}\right)\frac{1}{q_{-k}}\ \text{if} c_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}+} d^{-}_{c_{\theta_i^{\sim j}}} \\ 1-\left(\frac{|x_i - c_{\theta_i^{\sim j}}|}{d\theta_{i\ .}^{\sim j}}\right)\frac{1}{q_{-k}}\ \text{if} c_{\theta_i^{\sim j}} < x_i \le c_{\theta_i^{\sim j}} + d^{-}_{c_{\theta_i^{\sim j}}} \\ 0\ \text{if} x_i > c_{\theta_i^{\sim j}} + d^{-}_{c_{\theta_i^{\sim j}}} \text{or } x_i \le\ c_{\theta_i^{\sim j}} - d_{-\theta_i} \end{cases}$$

Where $\rho^{-}\theta_i^{\sim j}|_{us=q^{-k}}$ and $\rho^{-}\theta_i^{\sim j}|_{us=q_{-k}}$ are Fig. 4 noted as upper and lower membership, $\theta_i^{\sim j}$ mentioned as slice level of $u_s = q_{-k}$ and $u_s = qk$. $c_{\theta_i^{\sim j}}$ is the center function of different membership [3].

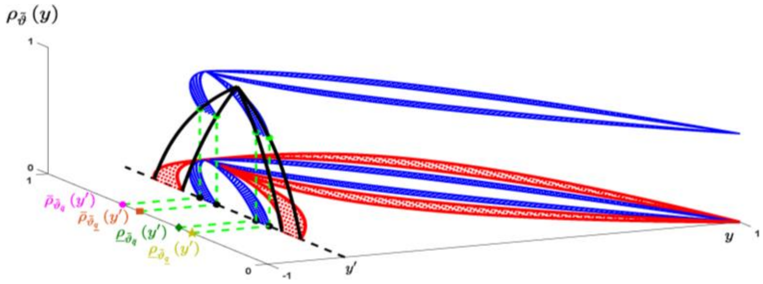


**Fig. 4:** Type-3 Membership Function.

To applied upper and lower membership levels as $u_s = q_{-k}, q^{-k}$ followed by

$$v_{qk}^{-l} = \rho^{\sim p1}_{\theta 1\,|us=q^{-k}} . \rho^{\sim p2}_{\theta 1\,|us=q^{-k}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \rho^{\sim pn}_{\theta 1\,|us=q^{-k}}$$

$$v_{q-k}^{-l} = \rho^{\sim p1}_{\theta 1\,|us=q_{-k}} . \rho^{p2}_{\theta 1\,|us=q_{-k}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \rho^{\sim pn}_{\theta 1\,|us=q_{-k}}$$

$$v_{-qk}^{l} = \rho^{\sim p1}_{\theta 1\,|us=q^{-k}} . \rho^{\sim p2}_{\theta 1\,|us=q^{-k}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \rho^{\sim pn}_{\theta 1\,|us=qk}$$

$$v_{-q-k}^{l} = \rho^{\sim p1}_{-\theta 1\,|us=q^{-k}} . \rho^{\sim p2}_{\theta 1\,|us=q^{-k}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \rho^{\sim pn}_{\theta 1\,|us=q-k}$$

Where lth rule is

If $x_1$ is $\overset{\sim\rho 1}{\theta 1}$ and $x_2$ is $\overset{\sim\rho 2}{\theta 2}$ and …………………..$x_n$ is $\overset{\sim\rho n}{\theta n}$

$y\varepsilon[\omega_{-l}, \omega^{-l}], l = 1, \ldots\ldots\ldots M$

Where $\omega_{-l}, \omega^{-l}$ contains the rule parameters
Output as,

$$f_1^{\wedge} = \sum_{K=1}^{K}(q_{-K}z_{-k} + q^{-k}z^{-k}) / \sum_{k=1}^{k}(q_{-k} + q^{-k})$$

Where

$$z^{-k} = \frac{\sum_{l=1}^{M}(u_{qk}^{-l}w^{-l} + v_{-qk}^{l}w_{-l})}{\sum_{l=1}^{M}(u_{qk}^{-l} + u_{-qk}^{l})}$$

$$z_{-k} = \frac{\sum_{l=1}^{M}(u_{q-k}^{-l}w^{-l} + v_{-q-k}^{l}w_{-l})}{\sum_{l=1}^{M}(u_{q-k}^{-l} + u_{-q-k}^{l})}$$

$$F_1^{\wedge} = \omega^T\varphi(x)$$

Where

$$\omega^T = [w_{-l}, \ldots\ldots\ldots\ldots, \omega_{-m}, w^{-l}, \ldots\ldots w^{-m}]$$

$$\mu\,(x) = [\mu_{-l}, , \mu_{-m}, w^{-1,}, w^{-m}]$$

$$\mu_{-l}(x) = \frac{1}{\sum_{k=1}^{k}(q_{-k} + q^{-k})}\sum_{k=1}^{k}\left(\frac{q_{-k}v_{-qk}^{l} + qk^{-}v_{-qk}^{l}}{\sum_{l=1}^{m}(v_{qk}^{-l} + v_{-qk}^{l}}\right)$$

$$u = \frac{1}{\propto^{\wedge}}\left[-KS - f_1\left(\frac{x}{w}\right) + r^{(n)}\right.$$

$$-\beta u - \gamma^{\int_0^t u\,(\tau)d\tau}$$

$$-|s|\tanh(s) + u1 + u_c$$

$u_1 = -\tanh(s)$

$u_c = -Sv\hat{}$

$\omega = ή \tanh(s)\varphi(x)$

$\propto^{\hat{}} = ή \tanh(S)\, u$

$v^{\hat{}} = ή\, |\tanh(s)|$

Where $\lambda i, k$ are the positive constantants. T3-FLS should be noted as

$x_1 = x_2$

Now consider the 3-FLS with Optimal parameters $f^{x\backslash w}$, S becomes

$$s = f_1(x\backslash w) + \propto^{u} + \beta^{u} + \gamma^{\int_0^t u(\tau)d\tau - r^{(n)} + \lambda_n e^{(n-1)}} + \cdots \ldots \ldots \ldots + \lambda 1e$$

$$+f_1\left(\frac{x}{w}\right) - f_1\left(\frac{x}{w}\right) + [f_1(x) + \Delta f_1(x) - f_1\left(\frac{x}{w}\right) + \alpha^{\sim}u + \beta^{\sim}u + \gamma^{\sim}\int_0^t u(\tau)d\tau + \varepsilon] \quad (2)$$

General AE as,

$$v_1 = [f_1(x) + \Delta f_1(x) - f_1(x\backslash w) + \alpha^{\sim}u + \beta^{\sim}u + \gamma^{\sim}\int_0^t u(\tau)d\tau + \epsilon$$

$$S = -ks + w^{\sim T}\varphi(x) + v + \alpha^{\sim}u + \beta^{\sim}u + \gamma^{\sim}\int_0^t u(\tau)d\tau - |s|\tanh(s) + u_1 + u_c$$

$$v \geq |v|$$

$$V_1 = -\frac{1}{ή} w^{\sim T}w - \frac{1}{ή}\alpha^{\sim} \propto^{\hat{}} - \frac{1}{ή}\beta^{\sim}\beta^{\hat{}} - \frac{1}{ή}\gamma^{\sim}\gamma^{\hat{}\hat{}}$$

$$+\tanh(S)S + u_1u_1 - \frac{1}{ή} v_1^{\sim}v_1^{\hat{}}$$

$$V_1 \leq -K|S| - \tan h^2(S)|S| + \tanh(S)u_c + |\tanh(S)||v| - \frac{1}{ή} v_1^{\sim}v_1\hat{}$$

$$V_1 \leq -K|S| - \tan h^2(S)|S| + \tanh(S)u_c + v_1^{\sim}\left[\left|\tanh(S)| - \frac{1}{ή} v_1\right] + |\tanh(S)|v_1\hat{}$$

$$V_1 \leq -K|S| - \tanh^2(S)|S|$$

$$-\int_0^t V_1(\tau)d\tau = V_1(0) - V_1(t) < \infty$$

$$\int_0^t K|S||\tanh^2(S)|S| < \infty$$

Followed by this equation $\int_0^t |S|^2 < \infty$. $S\epsilon l^2$, both values are considered as Barbalatt lemma provides the output as stable.

### 4.3. Particle swarm optimizers

It is a population-based search algorithm with individuals, or particles, that is optimized. Swarms are created from the groups [37]. Every particle stands for a potential fix for the optimization issue. In a PSO system, every particle moves through a multidimensional search space, modifying its location based on its personal interactions with nearby particles [17]. Optimal solutions are positioned by a particle using the best position it can find with its neighbor. As a minimum value found through the best solutions, the effect is recorded [18]. Each particle's performance near the global optimum should be evaluated since the optimization problem's features should be captured by the predetermined fitness function.

$$(p^t best_i = x_i \mid f_1(x_i) = \min_{k=1,2,\ldots,t}(\{f_1(x_i^k)\})$$

Where $i \in \{1,2, \ldots \ldots .., N\}$

$$g_{best}^t = x^t \mid F_1(x^t) = \min(\{f_1(x_i^k)\})$$

Where i=1,2,…….N and k = 1,2,……..,t
Where i noted as particle index, t is the current iteration, $f_1$ is the objective function that should be optimized, x is the position vector, N is the total number of particles present in PSO. To update the following equation the current iteration $t + 1$, velocity noted as v, position as x, each particle i followed by,

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_{besti}^t - x_i^t) + c_2 r_2 (g_{best}^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

To balance local and global exploitations, ω is the weight used, and V is the velocity vector. The range was uniformly distributed as [0,1] by the R1 and R2 random vectors. By analyzing equation (2) the particles are appropriately guided through the momentum and into the search space by the interia component and velocity [19].

### 4.4. Data flow diagram of proposed algorithm

The above Fig. 5 explains about data flow diagram of the type 3 fuzzy logic system, it is also called interval types-2 fuzzy logic, which is the extension of a traditional fuzzy logic system. To define the membership functions are allowed through modeling for one or more uncertainties in the system [34]. The inputs of this data flow diagram as membership functions. The next step is fuzzification, its used to convert the input values to fuzzy sets. This included the fuzzified membership functions followed by the possible ranges of values [28]. The rule-based fuzzy system as to apply the set of fuzzy references to interpret the relationship between the different fuzzy inputs. The inference mechanism is the engine processed through fuzzified input and fuzzy rules produce the fuzzy output values [29]. This involves various operations such as MIN or MAX. The aggregation output of the Type-3 Fuzzy system aggregated through the form of a single fuzzy set encapsulated through the possible output depends upon the uncertainty among the output membership functions. A defuzzification unit is used to convert the aggregated fuzzy output into input values. This type of flow diagram allows the type-3 fuzzy logic system to generate the output more accurately [30] [24].

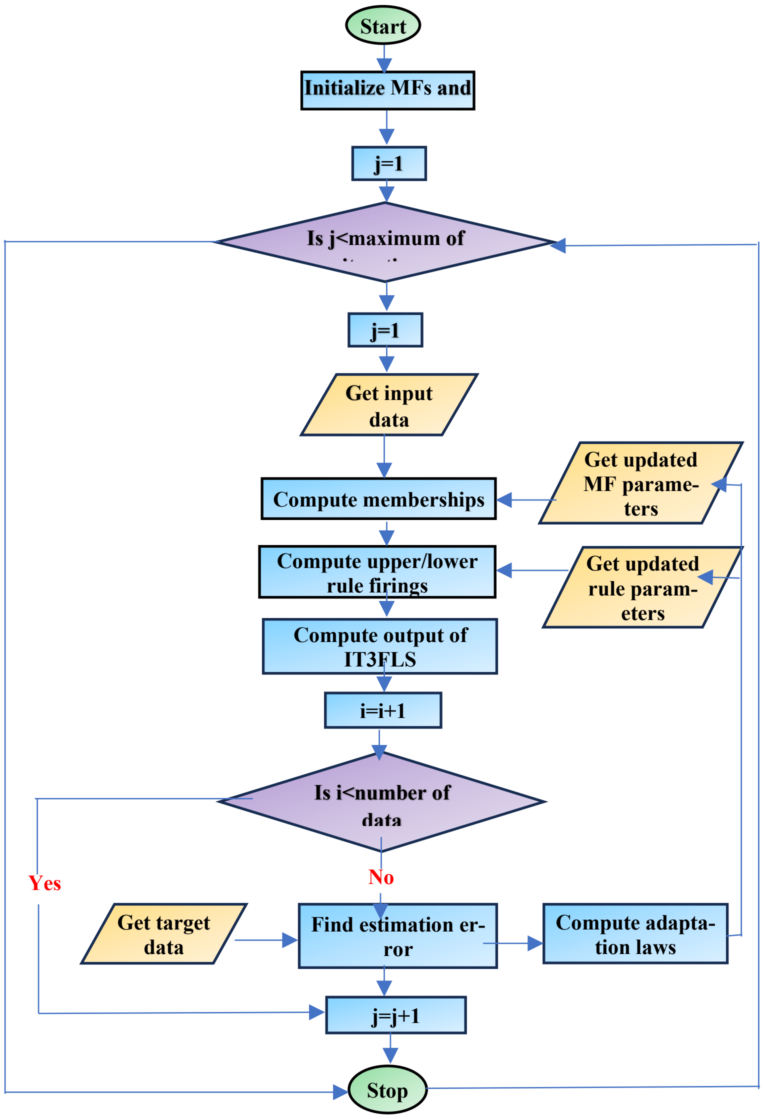


**Fig. 5:** Data Flow Diagram of Proposed Algorithm PSI-OT3FLRLA.

Proposed Algorithm: PSO-OT3FLRLA
Input
N-Swarm size
D-Problem dimensionality
T-Maximum number of iterations
LB- Lower bound
UB- Upper bound
Output

$g_{best}^{t}$ – Best solutions
Algorithm
Start
Initialize
for $i = 1$ to N do
$v_i^o \leftarrow$ Random vector$[LB, UB]^D$;
$x_i^o \leftarrow$ Random vector $[LB, UB]^D$;
$P_{besti}^{0} \leftarrow X_i^0$;
End for
Apply Equ (2) find $g_{best}^{0}$;
$t \leftarrow 1$;
While $t \leq T$ do
For $i = 1$ to N do
$r1, r2 \leftarrow$ two independent vectors randomly $[0,1]^D$
Apply Eqn (3)
Apply Eqn (4)
if $f_1(x_i^t) < f_1(P_{besti}^{t-1})$then
$f_1(P_{besti}^{t}) \leftarrow f_1(x_i^t)$;
End if
End for
Apply Eqn (2) find $g_{best}^{t}$;
$t \leftarrow t + 1$;
End while
End
Type-3 Fuzzy logic System
Start
Initialize MFS and rules
J=1
Get Input data
Compute membership function -> upper and lower rule
I = i+1
if $i <$ number of data
Yes-j = j+1
No- find estimate error→ compute adaptation laws
Applied Compute membership function
Stop

# 5. Results and discussion

## 5.1. Dataset details

This research selected the Dataset IAM, which contains the amount of handwritten tests for the training and testing phases. The data set includes 300 dpi greyscale images in Handwritten English. This research used line-level segmentation and used paragraphs for test validation and trained to split. The dataset includes each participant's handwriting, structured through line recognition followed by independent of participants. Next thing as used HTR data set contains 6161 images for training and 900 for validations, 1861 for testing. Here randomly selecting the example image from the RIMES dataset. The Employee's handwritten related to the business manager included the RIMES dataset. Greyscale images contain the French handwritten text followed by the settings of writing postal scenarios related to the RIMES handwriting dataset. These types of images have 300 dpi high resolutions. This research took 10,193 text used by training, 1133 lines for validations, and 778 lines for testing throughout the HTR system partitioning. Fig. 6 is noted as the Input Sample Dataset for RIMES and Fig. 7 describes as Output for RIMES Dataset.

**Fig. 6:** Input for RIMES Dataset.

RECEIVER VIA CATALOGUE DUO PRODUCTS PROPOSES

**Fig. 7:** Output for RIMES Dataset.

## 5.2. Analysis metrics

All reported results are subject to the following classifications are “recognition, error, rejection, and reliability rates”. Here noted as $N_{rej}$ as number of rejections, $N_{err}$ mentioned number of errors, and $N_{rec}$ noted as number of accurate classifications. After analysis, the recognition results as 100% accurate including with mistake rate and rejection rate. Followed by the practical setting to compute the rate as accurately followed by a handwritten recognition system. From the particular stage, the equation is used to calculate the recognition rate, error rate, and rejection rate.

$$\text{Recognition Rate} = \frac{N_{rec}}{N_B} \times 100$$

$$\text{Error Rate} = \frac{N_{err}}{N_B} \times 100$$

$$\text{Rejection Rate} = \frac{N_{rej}}{N_B} \times 100$$

$$\text{Relaiability Rate} = \frac{\text{Recognition Rate}}{\text{Recognition Rate+Error rate}} \times 100$$

### 5.3. Performance evaluation

Characters are selected from the database followed by legibility, this would entail eliminating characters that are too difficult to cursive from the test samples. This contains certain types of characters from the database followed by legibility. The entail eliminating types of characters are to difficult to see cursive from the test samples. Certain types of fonts in the database are written in cursive, which makes it very challenging to recognize the context. Twenty to thirty samples of each character are used to test the procedures. At the end of the system recognition rate should be mentioned as 94%. The Table 1 shows the information related to the classification rate among the dataset from the lowercase letters.

Followed by a Recognition rate of 92.45%, which provides a system that performs the overall and highly accurate values, which help to identify and classify data. It also related to a low level of error rate of 6.32%, suggesting that with occasional errors, the system should be generally reliable. The rejection rate of 3.31% noted as the system measured by this approach, contains the uncertainty or accuracy of the classifying data. It also decided to eliminate a small portion of data. This type of method helps to avoid inaccurate classifications with contains a high-reliability rate of 94.67%. This time system demonstrates dependability for correcting and classifying the majority of instances encountered.

The Table 2 shows that the recognition rate is compared through the previous OCRCHA recognition rate and the proposed Model of the PSO-OT3FLRLA category, which contains fuzzy rules and characteristics [31]. Compared to both models we suggest the proposed result is good and accurate, Ascending characters (b,d,f,h,k,l,t) are used for taller and simpler to recognize, which provides the result related to the OCR system as 94.72%. Descender characters (g,j,p,q,y) have an accurate result of 90.72%, neither category characters (a,c,e,m,n,o,p,r,s,u,v,w,x,y,z) are 86.96%, and both have a lower identification rate. It's closely similar to the height and structure. The system overall noted as the recognition rate as 89.45%, Which provides a positive for dealing with letters are have shorter or similar shapes. Fig. 6 shows the output of OCR [32].

**Table 1:** Performance Evaluation of the Proposed Model

| Data Group | Recognition Rate | Error Rate | Rejection Rate | Reliability Rate |
|---|---|---|---|---|
| Classification Result | 92.45% | 6.32% | 3.31% | 94.67% |

**Table 2:** Performance Evaluation on Character Grouping

| Character Grouping | Recognition Rate (%) OCRCHA | Recognition Rate (%) PSO-OT3FLRLA |
|---|---|---|
| Descenders Characters | 86.97 | 90.72 |
| Ascenders Characters | 90.68 | 94.72 |
| Neither Characters | 85.67 | 86.96 |
| Average | 87.87 | 89.45 |

**Table 3:** Performance Comparison with OCR Tools Converting Input Images into Text Documents Is the OCR Tool's Primary Purpose. Here, the Effectiveness of the OCR Tools Used with Various Approaches Is Compared.

| Sl. No | OCR Tools | Character Accuracy (%) | Character Error Rate (%) | Special symbol Accuracy (%) | Symbol error Rate (%) |
|---|---|---|---|---|---|
| 1 | Online OCR [1] | 95.9% | 4.10 | 0 | 100 |
| 2 | Free Online OCR [1] | 98.64% | 1.36 | 0 | 100 |
| 3 | OCR Convert [1] | 100 | 0 | 0 | 100 |
| 4 | Covert Image to text.net [1] | 100 | 0 | 0 | 100 |
| 5 | Free OCR [1] | 100 | 0 | 0 | 100 |
| 6 | I2OCR [1] | 100 | 0 | 0 | 100 |
| 7 | Free OCR to Word [1] | 23.29 | 76.71 | 0 | 100 |
| 8 | Google Docs [1] | 100 | 0 | 0 | 100 |

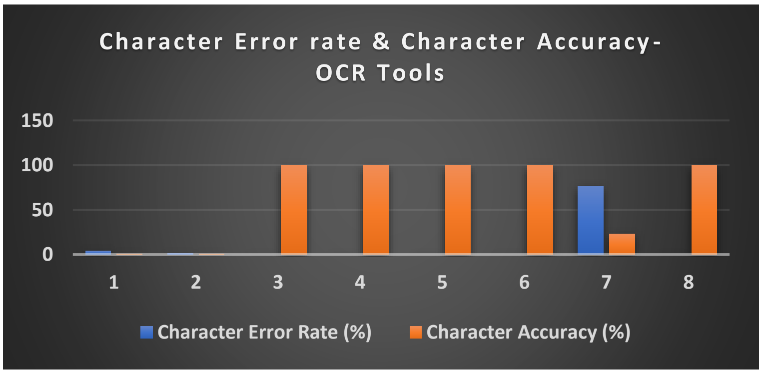


**Fig. 8:** Accuracy & Error Rate in OCR.

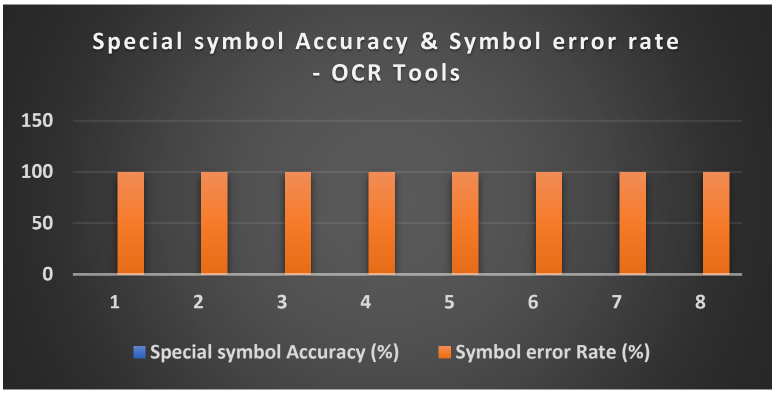


**Fig. 9:** Accuracy & Rate in OCR.

This Table 3 shows the accuracy and error rates among the different OCR tools. Also describes the character's accuracy. Character error rate, Special symbol accuracy, and Special symbol error rates. The Fig. 8 describes the overall character accuracy and error rate among the OCR tools. This Fig. 9 is observes by the performance of OCR converting image to text.net, google Docs, i2OCR, and better than the other tools. To measure the OCR tools, provide the accurate result 100% [1]. Character Accuracy of Online OCR as 95.9%. OCR converts as 100%. Free Online OCR is 98.64%, Free OCR is 100%, Free OCR to Word as 23.29%, and Google Docs is 100%. The symbol error rate of all types of the model is 100%

## 6. Conclusion

Particle Swarm Optimization (PSO) and Optimized Type-3 Fuzzy Logic combined provide notable improvements in accuracy and robustness for optical character recognition (OCR) systems, especially in the educational field. When it comes to identifying characters in noisy or ambiguous images a common occurrence in educational documents or handwritten notes Type-3 Fuzzy Logic offers an improved degree of uncertainty handling. The system gains better convergence speed and parameter tuning by combining this with PSO's optimization capabilities, which enables it to effectively adjust to a variety of document formats and handwriting styles. This hybrid approach enhances the OCR system's error-resilience and recognition rate, which improves real-time application performance. By using these optimized algorithms, OCR-based systems can also drastically cut down on the amount of manual corrections required, saving time and increasing productivity. It is also the best option for managing sizable educational databases with different document types due to its increased flexibility and scalability. In OCR applications, the integration of Optimized Type-3 Fuzzy Logic and PSO provides a strong and effective solution that can tackle the difficulties of identifying complex and varied educational content, ultimately advancing educational technology and online learning environments.

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