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Research on radar target recognition by fusion fuzzy logic algorithm

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Abstract: - For reliable identification and categorization of observed objects in radar systems, radar target recognition is a crucial job. In this study, we provide a method for identifying radar targets that uses a fusion fuzzy logic algorithm to increase identification precision. To deal with the uncertainties and imprecisions involved in target detection, the system combines input from several radar sensors and uses fuzzy logic methods. Inverse Synthetic Aperture Radar (ISAR) image-based classifiers are often combined or fused to examine complementary information. As a consequence, the findings from each classifier will be merged to increase the overall recognition rate. For this purpose, fusion methods are primarily used by automatic target recognition systems. This strategy is one of the most important current areas in target recognition research due to the empirical proof of its efficacy. The recognition combination will be described in this research utilizing fuzzy fusion based on three classifiers: Logistic Regression (LR), Artificial Neural Network (ANN), and Deep Convolutional Neural Network (DCNN) classifiers. To accomplish this goal, we have been using the Mamdani and Sugeno models. We have used an ISAR image database that was rebuilt from an anechoic chamber to increase the effectiveness of the suggested technique. It is intended to display every single result obtained from every individual classifier as well as the aggregated results. The proposed model has provided an accuracy and recognition rate of 97% and 94.6% respectively.

Keywords: Target Recognition, Inverse Synthetic Aperture Radar (ISAR), ISAR image, and Fusion Fuzzy Logic.

Research highlights

- Radar target recognition is a vital task for accurate identification and classification of detected objects in radar systems.
- In this research, we present a technique for accurately recognising radar targets by employing a fusion fuzzy logic algorithm.
- The system takes data from many radar sensors and applies fuzzy logic techniques to account for the inherent errors and imprecisions in target detection.
- Classifiers based on Inverse Synthetic Aperture Radar (ISAR) images are frequently fused together to look at related data.
- We have been employing the Mamdani and Sugeno models to achieve this end.
- To make the proposed method even more efficient, we have used an ISAR image database reconstructed from an anechoic chamber.
- Its goal is to show not only the overall results but also those produced by each individual classifier.

1. Introduction

Radar target identification, which includes detecting and categorizing objects based on their radar signatures, is an essential component of radar systems. Radio waves are used by the technology known as radar (Radio Detection and Ranging) to find and locate nearby objects. Target identification examines the radar returns and offers useful details about the kind, size, velocity, and other properties of identified objects [1]. Target identification will also be necessary for the military to enhance the evaluation of prospective threats, notably to positively identify an adversary. It will also be required to be significant in situational awareness and combat area management. An accurate and current local air picture will need to be provided. Information supremacy over prospective and current enemies will be aided by accurate target identification over a broad spectrum of military objectives and a big region [2]. Early danger detection gives you more time to respond. It makes it possible for the defense to adopt the proper defensive actions, such as using the best weapon systems, countermeasures, or evasive action. The best weapon may be assigned to the threat to increase the likelihood that it will be destroyed if it can be correctly categorized to its real target types, such as a specific aircraft or missile. Additionally, if the danger is a light aircraft, for instance, cannon fire may be sufficient to eliminate it rather than spending money on costly missiles that may only be available in limited quantities [3, 4].

It is important to determine if an engagement, such as one carried out by a close-range weapon system firing a missile at a dangerous air target, was effective and whether more missile launches would be necessary. To analyze

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the properties of any engagement debris and determine if the target or its remains still represented a danger, a high-resolution sensor would be required [5]. Even though target identification technology will be developed primarily for military applications, civil systems will benefit. The availability of a trustworthy target recognition capability in coastal surveillance and air traffic control systems would improve these systems and give more information to enable the proper response for policing the entry of illegal immigrants, smugglers, or terrorists into a country by land or sea [6]. The topic of automated target recognition (ATR) has seen a lot of effort over the years, from physical model-based approaches to statistical pattern identification methods.

The military has a clear need for efficient and effective ATR methods. If surveillance technologies could additionally give automatic, trustworthy classifications of the objects in the scanned regions, it would substantially improve our understanding of the battlefield. It is presently impossible to comprehend all the data due to the enormous amount that surveillance and ever-improving radar systems create [7]. The requirement for automated radar target categorization is growing in importance due to the widespread use of radar in military land, sea, and air applications, in part because it can be used in all types of weather. Radar target recognition uses various methods and algorithms to identify targets accurately and extract pertinent data from radar returns. These methods include multisensor fusion, artificial intelligence, feature-based recognition, machine learning, and signature-based recognition [8]. The kind of target present is identified using signature-based recognition, which matches the incoming radar signals with known signature databases. Signatures are distinctive patterns or characteristics that may be gleaned from radar returns and are specific to certain sorts of objects. The features vector is used to describe and categorize the actual class of a given target to complete the formal target recognition (classification) operation [9]. Perfect solutions are often difficult to get for radar target identification issues that include a high number of classes and noisy inputs. Recently, it has been discovered that classifiers of various kinds work best together when it comes to classification performance. This has led to the misconception that the optimal classifier may be discovered without thoroughly experimenting with all potential parameters. As a result, applying a classifier's fusion algorithms offers more effective recognition accuracy [10]. In this article, we present a classifier fusion model, specifically for LR, ANN, and DCNN classifiers, to improve target recognition task effectiveness.

2. Related Works

The research [11] suggested a deep Radar Object Identification Network (RODNet) to efficiently recognize objects only based on the well-processed radar resonance data in the style of Range-Azimuth Frequency Heatmaps (RAMaps). To anticipate the object confidence dispersion from every input RAMaps snippet, three distinct 3D autoencoder-based designs are presented. Traditional automobile radars transform raw data using digital signal processing (DSP) techniques into sparse radar pins that don't reveal the size or direction of the objects they are scanning for. A method for radar object recognition based on deep learning was presented in the publication [12]. The program processes radar data in its raw tensor form and generates probabilistic-orientated bounding boxes around the observed objects in bird's-eye view space. The research [13] employed the Intelligent Reflecting Surfaces (IRS) in the colocated Multi Input-Multi Output (MIMO) radar systems to raise the received power and improve the effectiveness of target detection, which was motivated by the increased capacity and energy performance of IRS in MIMO communication systems.

To address that, they provide an IRS-assisted target recognition technique that combines a useful IRS model for reflection optimization. The Deep Neural Network (DNN) is a well-liked classification subject effectively used in various scientific domains. DNNs have recently been suggested by various academics for use in radar applications. The research [14] examined the potential use of DNN- for target identification in radar, constructed DNN-based detectors, and contrasted the detector's performance with conventional target detectors. The research [15] suggested the first investigation into using Ultra-High Frequency (UHF) radar for ship target identification across rivers. The UHF radar's ability to identify ships is hampered by the broadening river clutters and water wave dispersion caused by the antenna's large beam width. Additionally, unlike the conventional point target signal, the ship echoes are significantly stretched in range and Doppler dimensions due to the high resolution. The Radar Region Proposal Network (RRPN), a real-time region proposal technique for object identification in autonomous cars, was presented in the article [16].

By mapping Radar identifications to the picture coordinate system and creating pre-defined anchoring components for each translated Radar detection location, RRPN creates object suggestions. To provide more precise suggestions for the identified items, these anchoring compartments are subsequently altered and resized by the object's proximity to the vehicle. By combining camera data and projecting fragmented radar data in the network layers, the research [17] improved the performance of existing 2D object identification networks. The suggested CameraRadarFusion Net (CRF-Net) automatically discovers the level at which the fusion of sensor data is most advantageous for the detection outcome. They also provide BlackIn, a training approach based on Dropout that concentrates learning on a particular sensor type. The crucial and difficult challenge in computer vision applications was real-world Inverse Synthetic Aperture Radar (ISAR) objects.

The paper [18] proposed a powerful real-world ISAR object identification technique. Called real-world ISAR object recognition, it is based on Deep Multimodal Relation Learning (DMRL). Radar image interpretation research has often focused on target detection in Synthetic Aperture Radar (SAR) images. Three widely used methods were utilized in the research [19] to provide adversarial examples that targeted three traditional deep learning systems for SAR image target detection. To accurately identify and count human targets inside a building, the research [20] provided a radar-based detecting processing system. This may be used to manage various presence-related loads in public, commercial, and workplace areas, as well as lighting, HVAC, and other appliances in smart homes. Applications for smart homes may help with energy conservation, control, and surveillance.

3. Methods

We discuss the three classifications used to categorize ISAR Images in this section. Then, Mamdani and Sugeno Model-based fuzzy system for decision fusion is presented and examined. The performance of each classifier is taken into consideration during the construction of a fuzzy fusion system, which is used to merge the results of numerous classifiers. Figure 1 depicts the multi-classifier fuzzy fusion system.

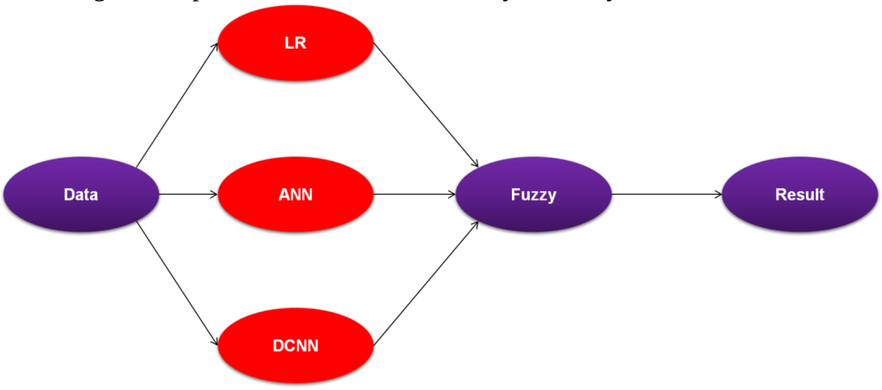

Figure 1: Fuzzy fusion system with several classifiers

The selection of the fuzzy model is supported by three main factors: The first advantage of fuzzy approaches is that they can account for the uncertainty and imprecision that comes with actual data. Secondly, there are so many options for fuzzy membership functions and combination operators, they also provide a lot of versatility. Finally, because fuzzy models are implemented using quick and simple operators, they are especially well-suited for practical applications.

3.1 Logistic Regression (LR)

When predicting target recognition based on the existence or absence of a certain radar, characteristic, or result in general using several independent explanatory factors of any sort (continuous, discrete, or categorical), we apply the regression technique known as logistic regression. Simple linear regression approaches fail to meet this requirement because they let the dependent variable exceed these bounds and provide inconsistent results. Still, the projected probability must be between 0 and 1. The probability that an item belongs to group 1 is defined as O_1, while group 0's probability is defined as O_0. The form of the logistic regression model is

$$y_j = \log\left(\frac{O_{j1}}{O_{j0}}\right) = a_0 + a_1 a_{j1} + a_2 a_{j2} + \cdots + a_l a_{jl} \tag{1}$$

O_{j1} / O_{j0} stands for the odds ratio, a_i for the ith coefficient's value, i=1,…,l, and w_{ji} for the ith predictor's instance values. The maximum likelihood technique calculates the logistic model's parameters (a_o to a_l). The logistic regression model may be used to determine the likelihood that an event will occur.

$$O\left(Z_j = 1 \backslash W_j\right) = \frac{f^{a^S W_j}}{1+\left(f^{a^S W_j}\right)} = \frac{1}{1+f^{-a^S W_j}} \tag{2}$$

Z_j stands for the event being studied (the dependent variable), and $f^{a^S W_j}$stands for the logistic regression function's linear indicator.

Suppose we employ a probabilistic threshold of .5. In that case, we may categorize an item as belonging to group 1 if the projected $O_1 > .5$ and to group 0 if $O_1 < .5$. The maximal likelihood approach maximizes the log-likelihood function metrics, a statistic that condenses the data of the predictor variables, to calculate the variables that make up the logistic regression framework.

3.2 Artificial Neural Network (ANN) radar target recognition

Several models of neural networks are created by connecting different radars to create an Artificial Neural Network (ANN), a conceptual model of radar target identification. A considerable number of layers are present in each of the hidden layers, input layers, and output layers in models of ANNs. The hidden layer simulates several sophisticated linear functions for nonlinear categorization using neurons. Nonlinear mapping's capacity may be improved by boosting the number of hidden layers.

The neural network's input phase uses the input stage to input the vector. After multiplying each element of the input matrix by its matching weight, the values are subsequently entered into the hidden layer through a linear overlay. The hyperbolic tangent curve and S-type functions are used as activation functions to preserve the nonlinear relationship between the input value and the output values in the buried layers. This increases the model's descriptive ability. This expression in mathematics looks like this:

$$\hat{z} = e(X \cdot W + a) \quad (3)$$

The weight group is represented by the higher form of X, whereas the stimulation factor and input matrix are indicated by E and W, respectively. The following expression describes the loss function of an ANN algorithm:

$$F(X) = \frac{1}{m}\sum_{j=1}^{m}(z_j, \hat{z}_j)^2 \quad (4)$$

In the equation above, $\hat{z}_j$ stands for the parameter's projected value, whereas z_j stands for the parameter's actual value. To acquire a collection of X weights and decrease the loss function to its smallest value, the loss function is utilized. The value of the loss function and simulation efficiency is inversely related. The accuracy decreases with increasing its value.

The gradient descent method is used in neural network training to adjust weight W during the reverse propagation. It contrasts the output of the neural network's actual and anticipated values. They differ from one another. The loss function or additional variables may be used to calculate the gradient separation along the line of the hidden layers, and errors are averaged out and assigned to each layer. Every level of neurons may utilize this error to change weight. This is known as the chain generation rule in mathematics. If the number and duration of iterations satisfy the criteria, either continue iterating until the issue is resolved or cease developing the network model.

3.3 Deep Convolutional Neural Network (DCNN)

An input layer, a convolutional layer, a pooling layer, and an output layer make up most of a DCNN, a multilayer neural network. Two instances of hidden layers are the convolutional layer and the pooling layer. The initial input image's pixel values are initially sent to the input layer of a DCNN network. The convolution layer then uses a convolution kernel to extract information from the picture. The required data is then divided into the pooling layer by the concept of the local correlation. The output layer then associates the feature with the labels.

Since the translation in DCNN is a forward propagation manage, which depicts the flow of data through the whole neural network from its input layer to its output layer, the output of the upper layer is the input of the current layer. Neurons from each layer must be introduced to a forward mechanism activation function that is nonlinear to avoid the flaws of the linear approach. There are no activation mechanisms in the initial layers because it merely gets pixel values from the image. The output of the k^{th} level may be stated as follows when the second layer's nonlinear activation functions are used:

$$\left.\begin{array}{l} y^k = X^k * w^{k-1} + a^k \\ b^k = \sigma(y^k), \end{array}\right\} \quad (5)$$

Where * denotes a convolution operation and k denotes the k^{th} layer. When k = 2, the image matrices $w^{2-k} = w^k$ (whose members are pixel readings) is used, and when k > 2, the feature map matrix w^{k-1} or $w^{k-1} = b^{k-1} = \sigma(y^{k-2})$is used, which is retrieved from the $(k-2)^{th}$ layer. The bias matrix, weighted input, and weighting matrices of the k^{th} layer are, accordingly, denoted by the letters X^k, b^k, and y^k, while indicating the nonlinear activating constant. Since K is the output layer, the real output matrix bK represents the last.

The quadratic function is often used as the error cost function. However, if the neurons commit an evident error during training of the DCNN, it would take a lot of time. Therefore, we use cross-entropy F_0^K as the error cost function rather than a quadratic function. The cross-entropy may be deduced from the forward propagation technique (Equation 6) as follows:

$$F_0{}^K = \frac{1}{m}\sum_{j=1}^{m}\sum_{l=1}^{M}[s_l^K ln b_l^K + (1 - s_l^K) ln(1 - s_l^K)] \quad (6)$$

Where M is the number of layers in the output layer, and m is the total amount of training sets. As a result, DCNN is eventually separated into M classes. The l^{th} neuron in the output layer's output layer is represented by s_l^Kas as the intended value and b_l^K as the actual output value.

3.4 Fuzzy Fusion Technique

The purpose of introducing fuzzy logic was to illustrate the powerful framework that can be used to manipulate imprecision in real-world situations.

We employed fuzzy rules and linguistic concepts for knowledge representation to integrate uncertainty argumentation. However, combining the support sets of the linguistic words involved in the subsequent active rules produces a fuzzy set with an assistance set (and therefore uncertainty/imprecision) in all cases for fuzzy rule base inferences.

Fuzzy sets may be seen as membership functions μ_w that assigns a number $\mu_w(W)$ in the interval to each component w of the universe of discourse U.

$$\mu_w: V \to [0,1] \quad (7)$$

This inherent flaw in fuzzy rule-based inference makes it difficult to interpret the resulting fuzzy sets. It prevents us from using them for other purposes, such as representing uncertainty propagation or creating new linguistic terms for the consequent when the size of the resulting support set is significant.

The groups of statements that comprise the fuzzy rule base are an essential component of the fuzzy logic scheme shown in Figure 2.

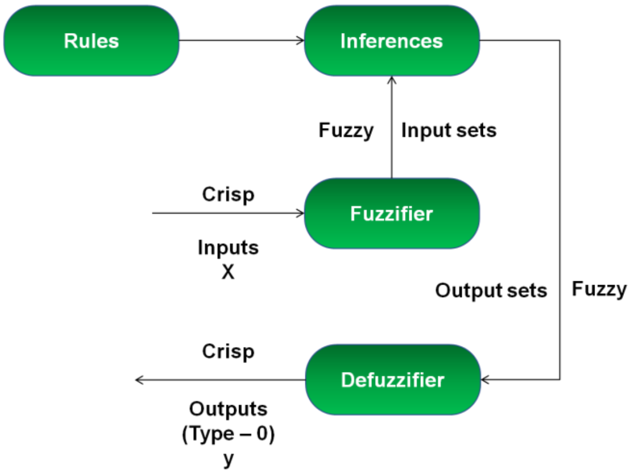

Figure 2: The fuzzy logic technique's design

The fuzzifier translates the aggregating output fuzzy collections to a crisp point in the resultant space. In contrast, the fuzzifier applies crisp inputs to fuzzy sets established on the input space. The Singleton fuzzifier is the most commonly used due to its ease of usage and little computational demands. The Mamdani and Segueno Models are two fuzzy frameworks used in constructing the suggested fusion system.

3.5 Fuzzy Fusion by Mamdani Model

The first fuzzy fusion mechanism is created using the Mamdani Model, in which fuzzy sets represent the results of fuzzy rules. For example, the fusion system that combines three classifiers has one output that represents the final determination from the fusion system and three correctness inputs that reflect the three classifier recognition rates (b_j) for each classifier (LR, ANN, and DCNN).

Simple triangles specify the input and output Membership Functions (MFs). Three fuzzy sets labeled "Low, Medium, and High" characterize each b_j input. The accuracy measurement identifies low level as 0–40%, medium level as 20–80%, and high rate as 60–100%.

There are 27 rules (33 = 27), each corresponding to one of 27 permutations of three inputs. The following is the definition of the ith fuzzy rule (i = 1... 27):

$$if\ b_1 is\ B_{j1}\ and\ b_2\ is\ B_{j2} and\ b_3\ is\ B_{j3},$$
$$THEN\ r_j\ is\ P_j(j = 1 \dots 27) \tag{8}$$

Where b_j (which may be either a linguistic phrase or a number) stands for the jth input rate of recognition (j=1... 3). For the Low, Medium, and High rules, $B_{ji}(i = 1 \dots 3)$ stands for the fuzzy input set, and h_j for the jth rule's output fuzzy set.

The system output is determined by adding the contributions of each rule:

$$y = \sum_{j=1}^{27} \beta_j h_j / \sum_{j=1}^{27} \beta_j \tag{9}$$

Where h_j denotes the jth rule's output value, and β_j denotes the ith rule's discharge rate as determined by the product t-norm:

$$\beta_j = \prod_{i=1}^{3} \mu_{B_{ji}} b_i \tag{10}$$

Where μ_{Bji} represents the degree to which input b_j belongs to the fuzzy sets B_{ji}.

3.6 Fuzzy Fusion by Segueno Model

Different fusion operators are generalized by the fuzzy integral. Three components are shown in the mathematical formulation of a fuzzy integral. $g_j(w_j)$ stands for the values to be integrated, where j=1,..,m, and n is the number of information sources. $\mu(B_j)$ stands for the membership functions utilized in the operator and the coefficients of the fuzzy measures. The third component is the fuzzy associations utilized to operate the first two components.

The kind of fuzzy integral depends on the fuzzy connectives utilized. Although there are many different kinds of fuzzy integrals, only two of them have seen widespread usage in practical settings. The first one takes advantage of fuzzy connectives, which have maximum and minimum operators. The Segeno Fuzzy Integral, which represents this integral, has the following phrase;

In contrast, the Choquet Fuzzy Integration uses the product (.) and the sum (Σ), according to:

$$T_\mu[w_1, \dots, w_n] = \sum_{j=1}^{m} \left[g_{(j)}(w_j) \wedge \mu\left(B_{(j)}\right)\right] \tag{11}$$

Where $\mu\left(B_{(0)}\right) = 0$. In the radar target detection process described here, $w_j \forall_i = 1,2,3$ stands for the collection of decisional components (classifiers) used in fusion, g_j quantifies the categorization decision made by classifier w_j

regarding the membership of the unidentified target to a particular class, and $\mu(B_j)$ represents the membership degree produced from every categorization rate's classifier.
A fuzzy measure μ offers a 2^m coefficient μ_{B_j} $\forall_i = 1, \dots 2^m$ that allows for forming several subsets B_j from the input classifier identification rate. Only n out of all these elements are considered by every fuzzy integration.

$$d_\mu[w_1, \dots\dots, w_n] = \sum_{j=1}^{m} g_{(j)}(w_j)[\mu(B_{(j)}) - \mu(B_{(j-1)})] \quad (12)$$

Following the sorting procedure indicated by the enclosing subindices in the phrases above, these are chosen. For instance, if $w_3 > w_2 > w_1$ is the input for the three classification rates, $w(1) = w_3$, $w(2) = w_2$, and $w(3) = w_1$. This process entails accounting for the coefficients $\mu(\{w2\})$, $\mu(\{w2, w3\})$, and $\mu(\{w1, w2, w3\})$.
The following characteristic of any fuzzy measure μ may be used to determine the fuzzy measure μ_{B_j} recursively:

$$\mu(B_{(j)}) = \mu(\{w_1, \dots., w_n\}) \forall i = 1, \dots, n1 \quad (13)$$

$$\lambda + 1 = \prod_{i=1}^{m} (1 + \lambda\mu^j) \quad (14)$$

After calculating the fuzzy measure, we can use equation (10) to determine the fuzzy integral T_μ for every category.

$$w \epsilon D_l \Leftrightarrow \mu_l = max_j[\mu_i(w)] \quad (15)$$

Determining each target's participation using combination operators (t-norm, t-conorm, median...) is the next and last stage. Regardless of the operator, the ultimate selection is based on the highest membership coefficient.

4. Results and discussion

In the results below, we choose the training dataset for each classifier using cross-validation. The output of each classifier is then subjected to the fuzzy fusion method.
We prepare the validation data described below: Each n-fold training information is split into m-folds. The remainder of the data is categorized to get the validation accuracies, with one-fold of the data used as the validation data. The fuzzy fusion model's classifier accuracy inputs will be calculated using the average of m-fold categorization.

4.1 Dataset description

On two different types of data sets, namely radar data and Iris data, the efficacy of the methods mentioned above was evaluated.
The anechoic chamber at ENSTA Bretagne is used to collect radar data. It is called MUSIC-2D. 1 picture from 10 scaled-down (1: 48) data. Each of the following ten aircraft targets is represented by 160 photos: Apache, F-14, Rafale, Harrier, Tornado, F117, F16, DC-3, Jaguar, and Mirage.
The data are initially categorized using three classifiers based on the following criteria. We used a neuron with two hidden layers and a hyperbolic tangent transfer function for the LR classifier. The selected value of l for the ANN classifier is thus 12. Last, we selected a Gaussian Kernel with$\sigma = 2 - 2$, 63, and $D = 2^{13}$for the DCNN classifier.

4.2 Experimental environments

Using ANN, DCNN, and LR classifiers, the data in phase I of the model are categorized. Three classifiers are combined using a fuzzy classifier system constructed in a Matlab application. Each classifier's decisions were established by optimizing them for each performance measure over the validation data; hence, a classifier may have various degrees of accuracy for every performance measure. This guarantees that the basis classifiers inside the fuzzy fusion system are as competitive as feasible.

4.3 Experimental results

We demonstrate the outcomes of classifying radar and iris data using firstly separate classifiers (LR, ANN, and DCNN) following previously specified variables and, secondly, fuzzy fusion using Sugeno (FF1) and Mamdani (FF2) Models.

Accuracy

The capacity of a radar system or program to accurately detect and categorize targets or objects in a radar picture is referred to as accuracy. It shows the proportion of properly categorized targets among all the examined targets. The accuracy assessment of classifiers and fusion approaches is shown in Figure 3 and Table 1.
The formula used to determine the accuracy metric is as follows:

$$\text{Accuracy} = \frac{\text{Number of correctly classified targets}}{\text{Total number of targets}} * 100 \quad (16)$$

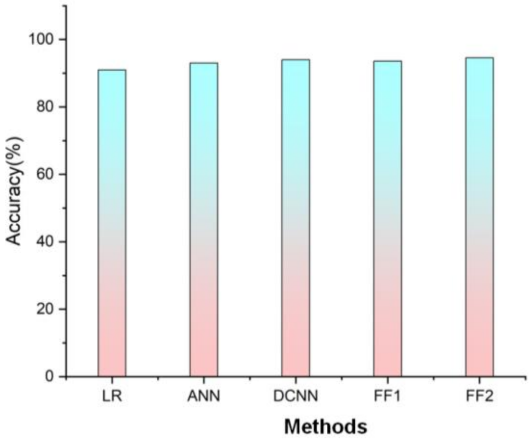

Figure 3: Accuracy evaluation of classifier and fusion techniques

Table 1: Accuracy evaluation

Methods	Accuracy (%)
LR	91
ANN	93
DCNN	94
FF1	93.6
FF2	94.6

The target identification system that is more accurate and dependable will have a higher accuracy value. It suggests that a greater percentage of objects in the radar picture are being accurately identified and classified by the system.

Precision

The capacity of a radar system or program to correctly detect and categorize objects as positive when they are, in fact positive is known as precision. Out of all the targets the system or algorithm categorized as positive, it reflects the percentage of targets accurately classified as positive. The precision assessment of classifiers and fusion approaches is shown in Figure 4 and Table 2.

The following formula is used to determine the precision metric:

$$\text{Precision} = \frac{\text{Number of true positive targets}}{(\text{Number of true positive targets} + \text{Number of false positive targets})} * 100 \qquad (17)$$

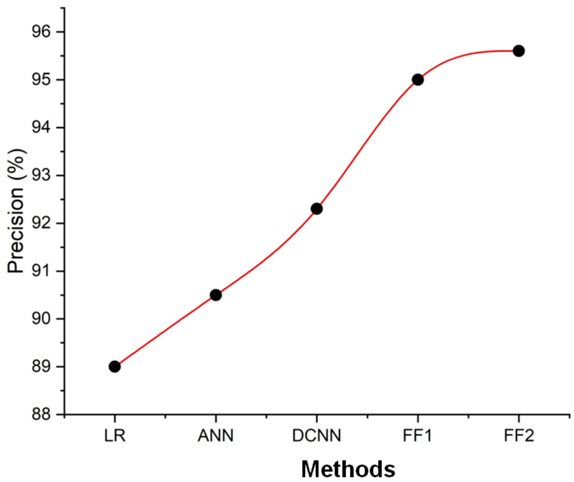

Figure 4: Precision evaluation of classifier and fusion techniques

Table 2: Precision evaluation

Methods	Precision (%)
LR	89
ANN	90.5
DCNN	92.3
FF1	95
FF2	95.6

A lower percentage of false positives suggests a system or technique that is more accurate at recognizing and categorizing targets as positive, as is the case with a greater precision value.

Recall

Recall describes a radar system's or algorithm's capacity to distinguish between and categorize each of the real positive targets in the radar perspective. It shows the percentage of targets that were positive and that the algorithm or system effectively identified. The recall assessment of classifiers and fusion approaches is shown in Figure 5 and Table 3.

The formula below is used to determine the recall metric:

$$\text{Recall} = \frac{\text{Number of true positive targets}}{(\text{Number of true positive targets} + \text{Number of false negative targets})} * 100 \quad (18)$$

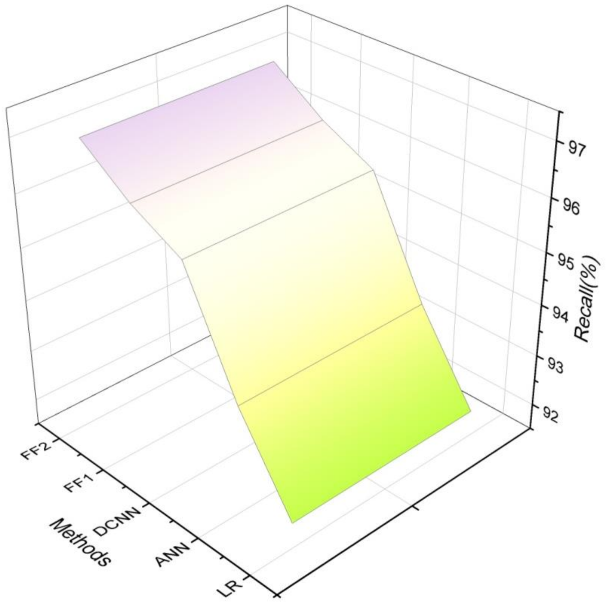

Figure 5: Recall assessment of classifiers and fusion techniques

Table 3: Recall evaluation

Methods	Recall (%)
LR	92
ANN	93.6
DCNN	95.7
FF1	96.2
FF2	96.9

The greater recall value suggests a lower incidence of false negatives, which suggests that the system or algorithm has a better degree of sensitivity in identifying affirmative targets. It implies that a greater percentage of the real positive objects in the radar picture are being efficiently captured by the system.

Recognition rate

The recognition rate describes how well a radar system or program performs in accurately recognizing and categorizing targets in a radar picture. It shows the proportion of targets that the system effectively detects and accurately categorizes. The assessment of the recognition rate of classifiers and fusion approaches is shown in Figure 6 and Table 4.

The following formula is used to determine the recognition rate metric:

$$\text{Recognition rate} = \frac{\text{Number of correctly classified targets}}{\text{Total number of targets}} * 100 \quad (19)$$

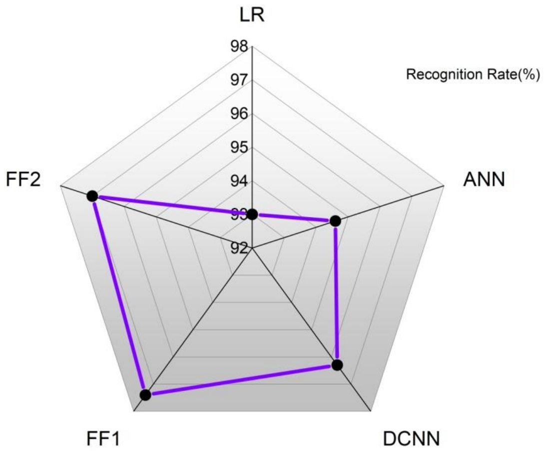

Figure 6: Recognition rate assessment of classifiers and fusion techniques

Table 4: Recognition rate evaluation

Methods	**Recognition Rate (%)**
LR	93
ANN	94.6
DCNN	96.3
FF1	97.4
FF2	97

Increased accuracy in target identification is shown by a higher recognition rate number, which suggests that a greater percentage of targets in the radar picture are properly identified and classified by the algorithm or system. In contrast, a lower number for the recognition rate indicates a greater rate of misclassifications or inaccurate target identification.

4.4 Performance analysis

The findings demonstrate that the fuzzy fusion outperforms the average of three independent classifiers in each of the four tests. Another significant finding is that in certain tests, the fuzzy classifier fusion model performs better and achieves greater accuracy than the best of the three separate classifiers that make up the model. In general, the Sugeno model, through fuzzy integral, outperforms the Mamdani model because the membership function of the latter model is characterized by more parameters than the former, making it more costly to attempt all potential values tailored to a specific set of data before selecting the best one. The fuzzy integral model can handle uncertainty better.

We must underline before we conclude this part that implementing fuzzy fusion to iris data is not as critical as it is to radar data. Both independent classifiers (LR, ANN, and DCNN) and fusion approaches exhibit almost the same accuracy, precision, recall and recognition rate. This indicates that the outcomes of classifiers lack both complementarity and variety. In addition, as compared to Iris data, radar data exhibits more flaws in the form of uncertainty and imprecision. Individual classifiers' varying recognition rates serve as a reflection of these flaws. The same classifier indeed outperforms others in specific validation data, but not in all. This indicates the lack of a top classifier and a universal classification approach for various data types.

5. Conclusion

The potential of data fusion to provide more precise answers makes it an essential tool for solving various technical challenges. The use and execution of data fusion based on the lowest level and the decision level have been extensively documented in the literature. We introduced a brand-new method for combining the classification results from ISAR photos with radar target identification. Our approach uses fuzzy models (Mamdani and Sugeno) and is decision-based. Results from experiments increase recognition rates. Future research will include confirming the findings with more data and looking at other combinations.

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