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Intelligent Military Aircraft Recognition and Identification to Support Military Personnel on the Air Observation Operation

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***Abstract*—A hostile or unfriendly aircraft will mostly fly at low-level altitude or hide behind natural obstacles to avoid Radar detection. One of the ways to detect and recognize while at the same time identifying such aircraft is to perform air observation from the ground. A technique called Visual Aircraft Recognition (VACR) has been practiced in training soldiers to recognize and find an incoming aircraft from a distance using binoculars. Remembering so many types of aircraft have their challenge. To ease the task, we have designed and developed an intelligent military aircraft recognition and identification system using the combination of Back Propagation Neural Networks (BPNN) and Information Fusion to speed up the recognition and identification. We use 13 aircraft features fused into five primary ones as the inputs to the BPNN for the recognition, while the identification uses Hamming Distance to the recognition results. With 155 data consisting of 85 military aircraft and helicopters and 70 civilian aircraft and helicopters and applying the 80:20 scheme for the training and test data, our system can obtain 95.33% and 87% accuracy at the training phase and the test phase. It also succeeds in recognizing and identifying a new military aircraft that is not in the dataset, while the Information Fusion can speed up the recognition and identification by up to 6 seconds. This impacts the acceleration of aircraft recognition and identification.**

***Keywords*— Artificial intelligence; backpropagation network; hamming distance; information fusion; military aircraft; recognition and identification.**

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I. INTRODUCTION

Defending the nation's air sovereignty requires a team of fighter aircraft, RRadar is the eye of the sky watching all aircraft and helicopters, or simply just aircraft flying in the nation's space-time by time. The Radar will detect and recognize any aircraft if they are flying within its coverage. Hostile and unfriendly aircraft will always avoid Radar detection by flying at very low altitudes or Nap-on-Earth (NoE) [1] or hiding behind natural barriers such as mountains or hills, as depicted in Fig. 1, before doing something deadly. This is also called a Radar shadow [2].

The applications of Artificial Intelligence (AI) technology to the military field are not new. Neural Networks (NN) method has been explored for air combat training in the context of its usage for the aircraft's avionics system [3]. It was also studied for its possibility as a flight control system to handle an aircraft when it experiences failure during flight. The emergence of various AI methods, especially those categorized as machine learning, has brought hopes that they can be used to give solutions to real-world problems such as classify data, make decisions, estimate future phenomenon, increase the efficiency of systems performance, and detect a suspicious condition that may proceed to a system failure [4], [5], [6], [7], [8].

One of interesting applications of AI in military field is to recognize and identify objects as an important part of surveillance operation [9], [10], [11], [12]. There have been some studies carried out to give solutions in detecting, recognizing as well as identifying aircrafts not only for military purposes but also for civilian ones [13], [14], [15],

[16], [17]. Some of the proposed solutions that utilize AI approaches are as follows.

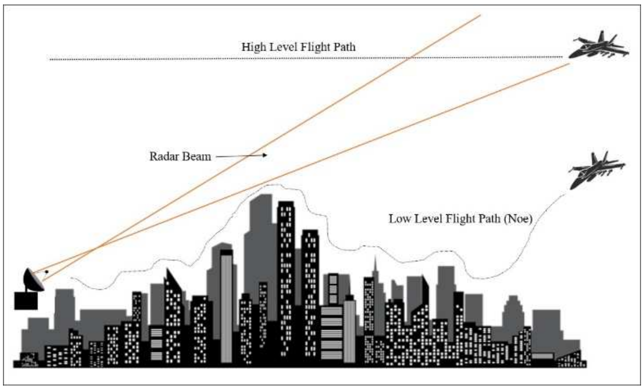

Fig. 1 The below aircraft is flying at the low altitude to avoid Radar detection and recognition

1) Aircraft Recognition or Classification Using Neural Networks-Based Model: Some examples of this category are Back Propagation Networks (BPNN) from remote sensing data and the combination of two kinds of Convolutional Neural Networks (CNN), namely modified U-net and RetiaNet architectures by using aircraft images [16]. CenterNet algorithm with TensorRT [18] is used for non-manned aircraft or drone identification. Proposed solutions also use a combination of four neural networks. Deep Convolutional Neural Network (DCNN) with the use of Principal Component Analysis (PCA) for feature selection [19] and detection and recognition with Single Shot multi-box Detector (SSD) network [20]. Other approaches, such as bilinear discriminative Extreme Learning Machine (ELM) network (BD-ELMNet) [21] is used for aircraft recognition, and Region-based Convolutional Neural Networks (RCNN) [22] is used for aircraft identification, which is done on remote sensing images.

2) Aircraft Recognition and Identification Using Non Neural Networks-Based Model: One of them is using a Support Vector Machine (SVM) classifier for Radar systems [23], object classification and identification using the information fusion capability of the Bayesian reasoning and also aircraft recognition and identification by utilizing the combination of Naive Bayes Classifier (NBC) and information fusion but using less number of aircraft characteristics, that is only nine ones [24]

All the solutions for the Radar system mentioned above do not give a solution if the Radar does not detect the object of interest because of performing NoE maneuver. Detection is the primary requirement before the recognition and identification process. The only way to detect, recognize, and identify such an incoming NoE aircraft from a distance is to assign soldiers to carry out observation from the ground with the help of binoculars. In this case, the soldiers must not only be able to operate the binoculars but also have enough knowledge regarding the types of military aircraft and their characteristics. Our approach here is not based on the aircraft images but on the observed aircraft characteristics observed by the observing soldier.

Remembering so many military types of aircraft's characteristic data while at the same time having to report to the ADS Command and Control post as quickly as possible is incredibly challenging. Investigating the problem at hand, in this research, we have designed and developed an intelligent military aircraft recognition and identification system based on BPNN by using the aircraft's characteristics listed in the US Army's Visual Aircraft Recognition (VACR) [24]. Even though BPNN has some deficiencies [25], NN-based machine learning is still the most widely used technique for classification [27], [28] which is the primary requirement for recognition. On the other hand, identifying the recognized object can be done using an information fusion technique. The NN-based method and information fusion [26] can improve the result of surveillance.

II. Material dan Methods

A. Visual Aircraft Recognition (VACR)

VACR becomes important when the available Radar system cannot detect the presence of military aircraft in their coverage areas. Failure to detect its presence will affect the inability to recognize and identify such aircraft, which can cause problems. Three kinds of military aircraft are based on their mission: friendly, hostile, or neutral. Therefore, recognizing and identifying a friendly aircraft as hostile, and vice versa, is a big problem because innocent people can be victims when the ADS receives false reports. The results of VACR can give much confidence to the ADC Command and Control to decide the correct action.

VACR emphasizes the features of remotely recognizing and identifying aircraft and uses four primary aircraft characteristics for that purpose, namely Wing, Engine, Fuselage, and Tail, abbreviated as WEFT, with examples depicted in Fig. 2.

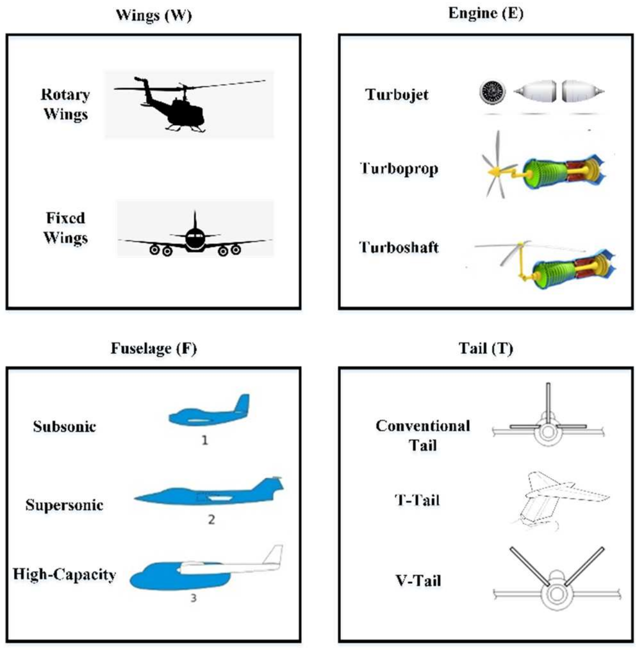

Fig. 2 Some examples of the aircraft's WEFT

Each primary characteristic has sub-characteristics as follows.

1) Wing (W): Wing is characterized by the following:

- The fixed-wing consists of high-mounted, mid-mounted, and low-mounted wing

- Variable geometry that consists of high-mounted, mid-to-low-mounted, and low-mounted
- Rotary that is characterized with:
  a) Main rotor mountings consist of single, dual, and coaxial
  b) Tail rotor mountings that consist of the right side and enclosed motor
- The taper consists of un-tapered, forward tapered, backward tapered, swept-back, diamond tapered, and swept-back and tapered wing
- The shape consists of the straight, swept-back, delta, and semi-delta wing
- The slant consists of the positive, negative, wingtip, and no slant wing
- Canard is a set of small wings installed at the forward part of the Fuselage.

2) Engine (E): The engine consists of jet and propeller-driven engines that are differentiated.

- The number can be one, two, three, or four engines
- The locations can be in-fuselage, behind the Fuselage, above the Fuselage, on tails, or on wings.

3) Fuselage (F): Fuselage is characterized by:

- The configuration consists of thick or wide, rectangular or boxed, tubular or round, and slender or tapered
- Canopy shape that consists of stepped, flush, and bubble.

4) Tail (T): Tail is characterized by:

- A number of tails that consists of a single, double, triple, and quadruple fin. The quadruple one is mostly related to a dish mounted above the Fuselage
- Fin shape that consists of equally tapered with a round tip, with blunt tip, with a curved tip, and with a square tip, black tapered with a square tip, swept-back tapered with blunt tip, round, and oval
- Shape and taper of tail flat that consists of back tapered with square tips and with round tips, equally tapered with a blunt tip and with a square tip, unequally tapered and swept-back with a square tip, delta-shaped with blunt tip, and rectangular
- The location or position of the tail consists of low-mounted, mid-mounted, high-mounted on the tail (T-tail), and low-mounted, mid-mounted, and high-mounted on Fuselage.

B. Backpropagation Neural Networks (BPNN)

Historically, a neuroscientist expert built the neural network model first by his logicism colleague in 1949. It is built to mimic how the biological nervous system works to solve some problems humans face in their daily lives. Various neural network-based architectures have been developed for numerous applications based on the original model. One of the famous neural networks is BPNN, a machine learning method that has been used for years for many applications [27], [28], [29], and shows a very good performance [30], [31], [32], [33], [34], [35], [36], effective [37], and accurate [38].

By mechanism, BPNN trains its network, which consists of many neurons, to find the balance between the network capability in recognizing the patterns given during the training mode and its ability to respond correctly to similar patterns used during the training mode. The BPNN training mode consists of three phases, as illustrated in Fig. 3, with the following explanation [39].

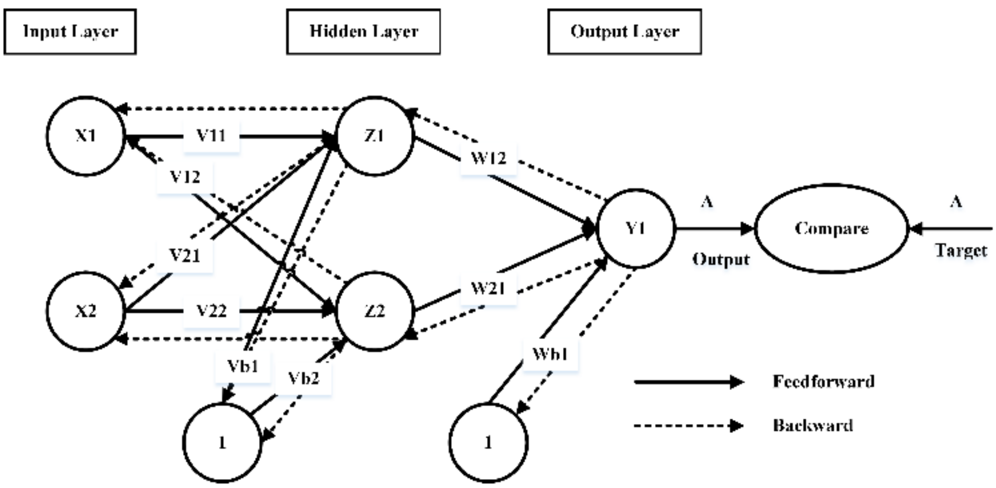

Fig. 3 The architecture of BPNN

1) Forward Phase: The input patterns are calculated forward from the input layer to the output layer with specific activation functions and corresponding weights. The results of the calculation are compared to the targets to obtain errors.

2) Backward Phase: The resulting errors obtained are then propagated backward, starting from the line that corresponds directly to the units in the output layer.

3) Weight Modification Phase: Based on the propagated errors, weight modification is carried out to reduce the errors. All weights will stop updating if the value of the error between the network's output and the target is very small according to the setup. The stabilized weights represent that the network already has representative knowledge.

C. Information Fusion

Information fusion is a way to obtain comprehensive information from many sources of information or multi-source information by combining all the information to become fused information [40], [41]. Information fusion aims to have knowledge that is extracted from such fused information. Information fusion in our research was inspired by the mechanism carried out by the brain to generate knowledge from the information sensed and perceived by at least two sensory organs [42].

Various modes for information fusion are viewed from the relationship between the input and output. Dasarathy [43] divided the mode into five categories that are simply explained as follows.

1) Data In–Data Out (DAI-DAO): The system processes the raw input data of an entity and results in raw output data. There is no feature extraction in this category, and the information within the data is not extracted, so there is not much knowledge that can be generated. The entity can be a phenomenon, object, or situation, whether physical or abstract.

2) Data In–Feature Out (DAI-FEO: The system extracts the feature(s) that consists of an entity's attributes or characteristics from the raw data. The features can be processed to obtain information regarding such an entity.

3) Feature In–Feature Out (FEI-FEO): In this scheme, the system can either refine or make better the existing entity features or obtain the new features of the entity from the existing ones.

4) Feature In–Decision Out (FEI-DEO): The entity features are processed to obtain a decision regarding it.

5) Decision In–Decision Out (DEI-DEO): A new decision can be extracted from the existing one. With this scenario, some alternative decisions can be combined to produce a better one.

D. Hamming Distance

Identification is the last step in Detection, Classification, Recognition, and Identification (DCRI), where the result of classification and recognition is presented. One of the methods that can handle binary numbers is Hamming Distance, requiring that the lengths of the two binary strings to be compared are the same [44]. The measurement is carried out by comparing the bits at the same locations. The distance between two binary strings is the total amount of different bits at the same position [45]. We select Hamming Distance for our system based on its good performance application for recognition as well as for decoding application where similarity is used as the primary measurement for the system or method performance [46], [47], [48], [49].

Hamming Distance is formulated in 1, where d_{ij} is the distance between the two binary strings, q is the number of bit with the value '1' in binary string i that has value '0' in binary string j, while r is the number of bit with the value '0' in binary string i that has value '1' in binary string j.

$$d_{ij} = q + r \tag{1}$$

E. Confusion Matrix

The common measurement to measure the performance of the classification carried out by a recognition and identification system is the confusion matrix [50], [51], [52], [53], which is a table that records all results of the classification results in a certain configuration as shown in Table I. The classification performance measurements are Precision, F1-Score, Recall, and Accuracy. Generally, four variables within the table are used to measure how good a classifier did its job, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) for binary classes [54], [55].

On the other hand, for multi-class problems such as the one we carried out, the variables and the formulas to measure the classifier performance by adapting [56] are as follows. Table I shows the generalized data distribution for the multi-class confusion matrix. Meanwhile, Table II shows the technique to show the distribution of the classifier's TP_{ii}, TN_{jk}. $FP_{i\neg i}$, and $FN_{\neg ii}$, as the values to measure its performance that consists of $Precision_i$. $Recall_i$, $F1-score_1$, and $Accuracy$. To show how it works, we created three variables, namely, A to represent the Actual Classes, P to represent the Predicted Classes, and V as the representation of the combined values of A and P while n is the number of classified data whether it is correct or incorrect, and i is the enumeration.

TABLE I
THE DISTRIBUTION OF THE CONFUSION MATRIX VARIABLES

Class		**Actual Class**				
		A_1	…	A_i	…	A_n
Predicted Class	P_1	V_{11}	…	V_{1i}	…	V_{1n}
	…	…	…	…	…	…
	P_i	V_{i1}	…	V_{ii}	…	V_{in}
	…	…	…	…	…	…
	P_n	V_{n1}	…	V_{ni}	…	V_{nn}

TABLE II
GENERALIZED CONFUSION MATRIX CONFIGURATION

Class		**Actual Class**				
		A_1	…	A_i	…	A_n
Predicted Class	P_1	TP_{11}	…	FN_{1i}	…	TN_{1n}
	…	…	…	…	…	…
	P_i	FP_{i1}	…	TP_{ii}	…	F_{in}
	…	…	…	…	…	…
	P_n	TN_{n1}	…	F_{ni}	…	TP_{nn}

1) TP_{ii} or True Positives: They represent the number of the data i, that were correctly recognized as true or positive. Simply, the Predicted Class, P_i were recognized as the Actual Class, A_i correctly.

$$TP_{ii} = V_{ii} \tag{2}$$

2) TN_{jk} or True Negatives: They represent the number of the data $\neg i$ or not-i, that were correctly recognized as false or negatives.

$$TN_{jk} = \sum_{j,k\neq i} N_{jk} = \sum_{j=1}^{n}\sum_{k=1}^{1} N_{jk} - (TP_{ii} + FP_{i\neg i} + FN_{\neg ii}) \tag{3}$$

3) $FP_{i\neg i}$: They represent the number of the data $\neg i$ or not-i, that were correctly recognized as true or positive.

$$FP_{i\neg i} = \sum_{k\neq i} N_{ki} = \sum_{k=1}^{n} N_{ki} - TP_{ii} \tag{4}$$

4) $FN_{\neg ii}$: They represent the number of the data i, that were correctly recognized as false or negative.

$$FN_{\neg ii} = \sum_{k \neq i} N_{ik} = \sum_{k=1}^{n} N_{ik} - TP_{ii} \quad (5)$$

5) $Precision_i$: The number of the data from Class i that were correctly recognized over the total number of the data that were predicted as true or positive, or it can be said as the ratio of TP_{ii} compared the overall positive predictions, $TP_{ii} + FP_{i \neg i}$.

$$Precision_i = \frac{TP_{ii}}{TP_{ii}+FP_{i\neg i}} \quad (6)$$

6) $Recall_i$: The ratio of TP_{ii} compared to all correct predictions.

$$Recall_i = \frac{TP_{ii}}{TP_{ii}+FN_{\neg ii}} \quad (7)$$

7) $F1 - score_1$: The comparison of the average value of $Precision_i$ and $Recall_i$, or it can be said as the harmonic mean of both values.

$$F1 - score_1 = \frac{2*(Recall_i * Precision_i)}{Recall_i + Precision_i} \quad (8)$$

8) $Accuracy$: the correct prediction result from all test data.

$$Accuracy = \frac{TP_{ii}+TN_{jk}}{TP_{ii}+TN_{jk}+FP_{i\neg i}+FN_{\neg ii}} \quad (9)$$

or

$$Accuracy = \frac{\sum_{i=1}^{n} TP_{ii}}{\sum_{i=1}^{n}\sum_{j=1}^{n} N_{ij}} \quad (10)$$

F. K-Fold Cross Validation

A technique to validate a classifier model is K-fold cross-validation [59, which is used for measuring how well the mode can predict or estimate [60] in terms of accuracy. In this technique, the data will be divided into K folds comprising the training data and the test data with the same size according to the selected number of K where K is larger than 1. The test fold will be moving to the next fold in each iteration, and the accuracy of the model is measured in each fold iteration. The model's accuracy is the average accuracy of all folds, namely the total accuracy divided by the number of folds (K) [58]. This validation method is also to ensure that the resulting model can produce unbiased [59], consistent [60], and reliable [61] recognition results, which will be followed up with their identifications. It is also used to check the resulting model's performance [2], [62].

III. Results and Discussions

Having all materials presented previously, in this section, the design and the implementation of the intelligent recognition and identification system will be delivered in a simple and orderly manner. It is started with a general view of how the system works, followed by the detailed flow in the form of a block diagram. The system training and testing results will also be given along with its performance measurement using a confusion matrix compared to K-fold cross-validation. An experiment with brand-new data will also be presented to show the system's performance.

A. Data

In this research, we used aircraft data from many sources to ensure the quality of the data. Our military aircraft data consists of stealth fighters and bombers, fighter and attack aircraft, and modern soviet warplanes, including their performance data [63]. After studying all available data, we selected 155 aircraft that comprise 45 military aircraft, 40 military helicopters, 35 civilian helicopters, and 35 civilian aircraft that are grouped into four classes, namely military aircraft, military helicopters, civilian helicopters, and civilian aircraft. Based on our study of all characteristics mentioned in Section II by selecting 13 characteristics that are the most differentiated features among the aircraft. An example of our processed military aircraft's characteristics dataset is presented in Table III to Table V. This example dataset consists of eight military aircraft from the United States and China.

TABLE III
SOME EXAMPLES OF PROCESSED MILITARY AIRCRAFT'S CHARACTERISTICS DATA PART 1 (CONTINUED)

Types of Aircraft	Type of Wing	Wings Placement	Number of Wings	Wings Direction
Military	Fixed	Mid	Monoplane	Sweptback
Military	Fixed	Low	Monoplane	Delta
Military	Fixed	High	Monoplane	Delta
Military	Fixed	Mid	Monoplane	Delta
Military	Fixed	High	Monoplane	Sweptback
Military	Fixed	High	Monoplane	Sweptback
Military	Fixed	Mid	Monoplane	Sweptback
Military	Fixed	High	Monoplane	Sweptback

TABLE IV
SOME EXAMPLES OF PROCESSED MILITARY AIRCRAFT'S CHARACTERISTICS DATA PART 1 (CONTINUED)

Types of Engines	Number of Engines	Engine Placement related to Fuselage	Fuselage	Types of Tail
Turbofan	1	Behind	Subsonic	Conventional
Turbofan	1	Behind	Subsonic	Conventional
Turbofan	2	Behind	Supersonic	Twin
Turbofan	2	Behind	Supersonic	Conventional
Turbofan	2	Behind	Supersonic	Twin
Turbofan	2	Behind	Supersonic	Twin
Turbofan	1	Behind	Subsonic	Conventional
Turbofan	2	Behind	Supersonic	Twin

TABLE V
SOME EXAMPLES OF PROCESSED MILITARY AIRCRAFT'S CHARACTERISTICS DATA PART 1 (CONTINUED)

Types of Landing Gear	Canard	Weapon	Color	Aircraft Name
Folded	No	Yes	Light Grey	Chengdu J-7
Folded	Yes	Yes	Light Grey	Chengdu J-10
Folded	Yes	Yes	Light Grey	Chengdu J-20
Folded	No	Yes	White	Shenyang J-8
Folded	No	Yes	Dark Grey	Shenyang J-11
Folded	No	Yes	Dark Grey	Shenyang J-16
Folded	No	Yes	Dark Green	F-16 Fighting Falcon
Folded	No	Yes	Black	F-15E Strike Eagle

B. The Model of the System

This system aims to assist the soldiers assigned to carry out ground observation when the available sensors cannot detect the presence of a suspected hostile military aircraft entering the sovereign air space. A suspected hostile military aircraft is detected entering the air space at a low altitude to avoid Radar detection. The observer soldier will carry out the air observation within a certain field of view to obtain the characteristics of the detected aircraft. He observes the aircraft's characteristics and speaks loudly one by one to his colleague soldier to enter them into the system. The detailed model of the system is depicted in Fig. 4.

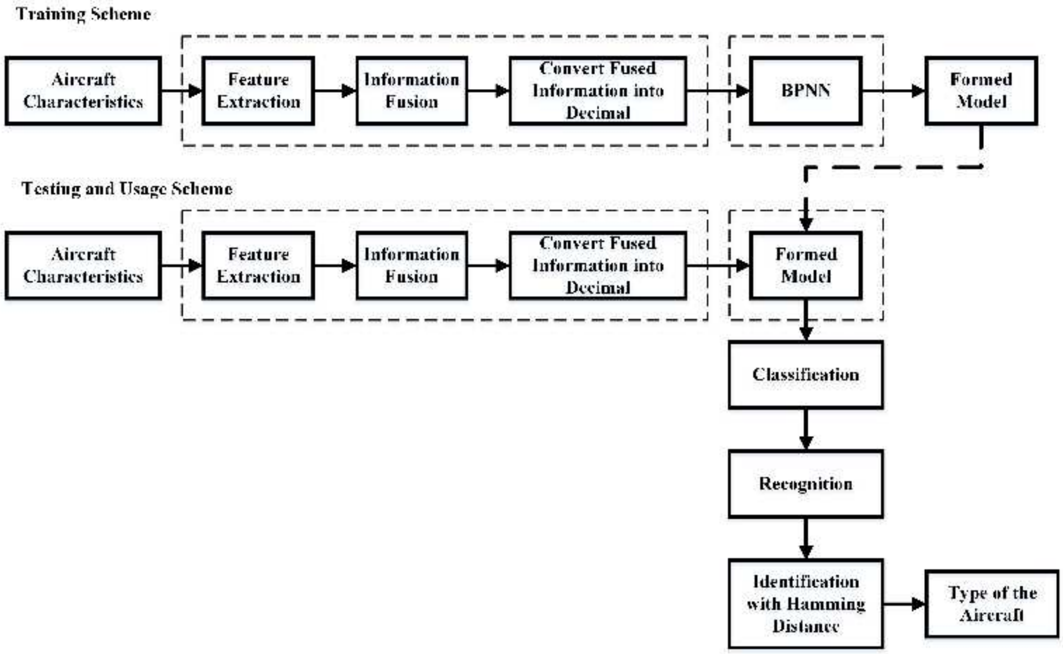

Fig. 4 Detailed model of the system that shows how BPNN generates knowledge

Within the system, all inputted characteristics will be converted into binary representations according to the conversion rules set up, adopting the concept brought by [64]. The binary conversion is a feature extraction technique following DAI-FEO mode. All binary representations are fused to obtain refined features representing all detected aircraft characteristics. This mechanism follows FEI-FEO mode of information fusion. The resulting fused features are inputted to *BPNN,* which will recognize the type of the detected aircraft, whether it is truly hostile, as suspected, or friendly or neutral. DAI-FEO and FEI-FEO modes encompass two levels of data abstraction in information fusion, namely Low-Level Fusion and Medium-Level Fusion [65].

TABLE VI
SOME EXAMPLES OF FEATURE EXTRACTION FROM THE AIRCRAFT CHARACTERISTICS

Types of Landing Gear	**Specific Parts**		**Extracted Feature (Binary Representation)**
Wing	Types	Rotary Wings	0000000000000001
		Fixed Wings	0000000000000010
Engine	Number of	One	0000001001000000
		Two	0000000110000000
		Three	1000000110000000
		Four	1000000110000010
Fuselage	Function	High-Capacity Subsonic	0000000010000100
		High Maneuverability Supersonic	0000000001000010
		Flying Boat	0000000000100001
		Dragonfly	0000000010001000

The tricky thing in the system is obtaining the proper features representing the aircraft's characteristics. Table VI shows lists of features we set up to represent the aircraft characteristics along with each extracted feature. As an example, we have set up the binary representation or the feature of the "Fixed Wing" characteristic as "0000000000000010". This characteristic and other observed characteristic will be fused to create refined features consisting of five primary features, namely WEFT, and one additional feature as depicted in Fig. 5. The fused feature for W consists of Types of Wings, Wings Placement Number of Wings, and Wings Direction. The fused feature for E consists of Types of Engines, Number of Engines, and Engine Placement. The fused feature for F only consists of the Fuselage, and T also consists of Types of Tail.

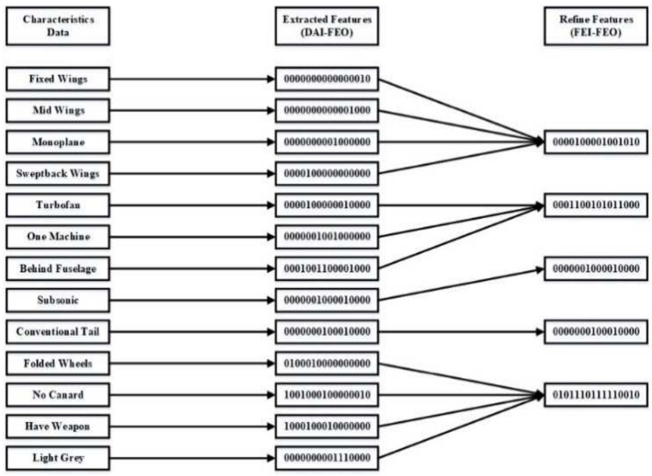

Fig. 5 Utilizing the information fusion to obtain five primary features as the inputs to BPNN

The fused feature for additional characteristics consists of Types of Landing Gear, Canard, Weapon, and Color of Aircraft. Before inputting to BPNN, those features will be processed by converting them into decimal numbers to normalize the binary features into their decimal representations. The BPNN hyperparameters, namely the hidden layer and learning rate, were also tested to find the most optimal values during the training scheme. The system performance was also measured during the two schemes.

C. Optimal Hyperparameter Values and System Performance Viewed from Accuracy, Speed, and Brand-New Data

1) Optimal Hyperparameter Values: The goodness of the BPNN model as a classifier and recognizer is determined by two hyperparameters, namely the number of hidden layer nodes and learning rate. Therefore, during the training scheme, the primary priority is to find the most optimal values of them. Table VII shows some results of our experiment with the number of hidden layer nodes from 50 to 400, and the learning rate from 0.1 to 0.6 by using 80% of the total data, which is 124 data.

TABLE VII
THE MODEL'S OPTIMAL HYPERPARAMETER VALUES AND ITS PERFORMANCE

Number of Hidden Layer Nodes	**Learning Rate**	**Accuracy**	**Mean Squared Error (SME)**
50	0.1	77.56 %	0.0055671
50	0.3	88.92 %	0.0005331
50	0.5	87.97 %	0.001619
50	0.6	89.31 %	0.002860
100	0.1	77.56 %	0.011504
100	0.3	90.54 %	0.001953
100	0.5	92.09 %	0.002092
100	0.6	93.85 %	0.000186
200	0.1	82.88 %	0.008420
200	0.3	92.78 %	0.000411
200	0.5	93.79 %	0.00088
200	0.6	94.07 %	0.00237
300	0.1	83.69 %	0.012354
300	0.3	92.59 %	0.001771
300	0.5	93.6 %	0.00238
300	0.6	95.33 %	4.3746e-05
400	0.1	86.33 %	0.00737
400	0.3	92.41 %	0.00127
400	0.5	94%	0.00022
400	0.6	94.6 %	0.0022

From the training scheme, we found that the most optimal number of hidden layer nodes is 300, while the most optimal learning rate value is 0.6. The combination of the two most optimal values resulted in the highest system performance with the accuracy of 95.33% with the lowest Mean Squared Error (MSE) of 4.3746e-05.

2) System Performance Viewed from Accuracy: After getting the most optimal hyperparameter values, we did the test to the system by using 20% of the total data, namely 31 data. Based on the results, we obtained that the system's accuracy is 87% taken from 27 true predictions divided by the total number of test data. In our system, the data is labelled with numbers 0 to 3 where label "0" is for military aircraft, label "1" is for civilian aircraft, label "2" is for military helicopter, and label "3" is for civilian helicopter. Table VIII compile all results as the means to measure all system performances through its Confusion Matrix.

TABLE VIII
THE CONFUSION MATRIX FOR THE MODEL'S TESTING RESULTS

Class		**Actual Class**			
		0	**1**	**2**	**3**
Predicted Class	0	**9**	1	0	0
	1	0	**6**	0	0
	2	0	0	**4**	3
	3	0	0	1	**8**

The next step is to measure the system performance by using 6 to 10 by using the values of TP_{ii}, TN_{jk}, $FP_{i\neg i}$, and $FN_{\neg ii}$. The subsequent table presents the values of all variables for all classes. The accuracy for predicting class '0' is 100%, class '1' is 100%, class '2' is 87%, and class '3' is 87%. Therefore, the average accuracy for all classes is 94% as shown in Table IX. This value is close to the system accuracy during the training scheme, that is 95.33%. The system can correctly predict class '0' and '1' which are military aircraft and civilian aircraft. However, it is also pretty good to correctly predict class '2' and class '3'.

TABLE IX
THE RESULTS FOR ALL RECOGNITION MEASUREMENTS

Class	**Precision**	**Recall**	**F1-Score**	**Accuracy**
0	1	1	1	1
1	1	1	1	1
2	0.80	0.57	0.67	0.87
3	0.73	0.89	0.80	0.87
Average	0.88	0.87	0.87	0.94

3) System Performance Viewed from the Processing Speed: The performance test is simple, that is by comparing the recognition and identification process by using 13 original features with 5 refined features. The results of the test are presented in Table X.

TABLE X
THE RESULTS OF SPEED COMPARISON TEST

Input Method	**Processing Speed**	**Accuracy**
5 refined features	40 second	95.33%
13 original features	46 second	96.56%

With the original features, the system can reach an accuracy of 96.56% better than that of the refined features, but with slower processing speed, 6 seconds slower. Because the concern is regarding the ADS, these 6 seconds are very meaningful in terms of the flying speed of military aircraft, especially fighter-type ones. It is a trade-off of a high-risk selection between the system recognition and identification's accuracy and the processing speed. The system's processing speed is more important than its accuracy for the ADS. Moreover, based on our test, the difference in accuracy between the two input methods is very low, which is 1.23%.

4) Validating the Formed Model: Even though we had used 80:20 scheme to train and test the system, we want to ensure that the Formed Model is the most optimal model for our system by comparing it with K-fold cross validation scheme. The comparison was done with K = 4, 6, 8 and 10, where the amount of data in each fold is around 39, 26, 19, and 15. The results of the validation are presented in Table XI.

TABLE XI
THE COMPARISON OF THE MODEL WITH THE K-FOLD ONES

K-Fold Cross Validation Scheme		80:20 Scheme Accuracy	
K	**Average accuracy**	**Training**	**Testing**
4	82.89 %		
5	83.23%		
6	86.66 %	95.33 %	87%
8	84.86 %		
10	78 %		

The highest average accuracy was K-fold cross-validation at 86.66% at K = 6. This value is very close to the accuracy obtained from the 80:20 testing scheme, which is 87%. This comparison has validated that the Formed Model shows consistent, reliable performance and unbiased results.

5) System Performance with Brand New Data: The last test is by giving the system a brand-new input that has never been introduced to the system whether in the training scheme or in the testing one. In this test, we use the characteristic data of Mirage III fighter aircraft as presented in Table XII

TABLE XII
THE MIRAGE III FIGHTER AIRCRAFT'S CHARACTERISTICS DATA AND ITS FEATURES

Characteristics	Specific Part	Extracted Features
Wings Placement	Low	0000000000010000
Number of Wings	Monoplane	0000000001000000
Wings Direction	Delta	0010000000000000
Type of Engine	Turbo Fan	0000100000010000
Number of Engine	One	0000001001000000
Engine Placement	Behind	0001001100001000
Fuselage	Supersonic	0000000100001000
Types of Tail	Conventional	0000000100010000
Types of Landing Gear	Folded	0100010000000000
Canard	No	1001000100000010
Weaponry	Yes	1000100010000000
Color of Aircraft	Stripes	0011100000000000

The result of the recognition and the identification is shown in Fig. 6. The system can correctly predict that the detected and recognized aircraft is identified as Mirage 2000 with the prediction accuracy of 67.75%.

Fig. 6 The result of system recognition and identification for the brand-new data

IV. CONCLUSION

Based on Results and Discussion section, our intelligent system for military aircraft recognition and identification based on the text data has shown a very good performance. It is shown by its ability to correctly predict military aircrafts and civilian aircrafts with accuracy of 100%, and it also has good performance to correctly predict military helicopters and civilian helicopters with accuracy of 87%.

In average, the accuracy of the system's recognition and identification is 93.5%. The use of information fusion can speed up the recognition and identification 6 seconds faster than that of not using information fusion. Such time is significant for the ADS that defend the sovereignty air space knowing that the aircrafts fly at high speed. The real test on a brand-new data has shown that our system is able to make generalization to recognize and identify the aircraft with very close prediction.

There are some further works that we have planned to do, as follows. The low accuracy of recognizing and identifying whether the helicopters are military, or civilian may be because of the lack of characteristics data. In the guidebook we use as the primary reference, the VACR characteristics for the helicopters are minimal compared to the aircraft, which are very complete. Even though we have added more characteristics data out of the reference book, the accuracy is still lower than the one for the aircraft. We will do more study to create more characteristics data for the helicopters. We plan to add data on Unmanned Aerial Vehicles (UAV) and drone that have similar characteristics to aircrafts and helicopters to enhance our system performance.

REFERENCES

[1] T. Nallusamy and P. Balaji, "Optimization of NOE Flights Sensors and Their Integration," in *Advances in Human and Machine Navigation Systems*, IntechOpen, 2019. doi: 10.5772/intechopen.86139.

[2] Avionics Department, *Electronic Warfare and Radar Systems Engineering Handbook 2013 NAWCWD TP 8347 Fourth Edition*. Point Mugu: Naval Air Warfare Center Weapons Division, 2013. Accessed: Jan. 23, 2022. [Online]. Available: https://apps.dtic.mil/sti/pdfs/ADA617071.pdf.

[3] C. Bowman, M. Deyong, and T. Eskridge, "Role of Neural Networks for Avionics," in *SPIE's 1995 International Symposium on Optical Science, Engineering, and Instrumentation,* 1995. [Online]. Available: http://proceedings.spiedigitallibrary.org/.

[4] P. Scharre, "Military Applications of Artificial Intelligence: Potential Risks to International Peace and Security," 2019.

[5] I. Szabadföldi, "Artificial Intelligence in Military Application – Opportunities and Challenges," *Land Forces Academy Review*, vol. 26, no. 2, pp. 157–165, Jun. 2021, doi: 10.2478/raft-2021-0022.

[6] F. E. Morgan et al., Military Applications of Artificial Intelligence: Ethical Concerns in an Uncertain World. 2020.

[7] Christian H. Heller, "Near-Term Applications of Artificial Intelligence," *Naval War College Review*, vol. 72, no. 4, pp. 73–100, 2019, doi: 10.2307/26775520.

[8] Zachary Davis, "Artificial Intelligence on the Battlefield," *Prism*, vol. 8, no. 2, pp. 114–131, 2019, doi: 10.2307/26803234.

[9] S. Pradeep and Y. K. Sharma, "Deep Learning based Real Time Object Recognition for Security in Air Defense," in *2019 6th International Conference on Computing for Sustainable Global Development (INDIACom)*, 2019, pp. 295–298.

[10] Z. Ozkan, E. Bayhan, M. Namdar, and A. Basgumus, "Object Detection and Recognition of Unmanned Aerial Vehicles Using Raspberry Pi Platform," in *2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 2021, pp. 467–472. doi: 10.1109/ISMSIT52890.2021.9604698.

[11] W. Budiharto, E. Irwansyah, J. S. Suroso, and A. A. S. Gunawan, "Design of object tracking for military robot using pid controller and

computer vision,” *ICIC Express Letters*, vol. 14, no. 3, pp. 289–294, 2020, doi: 10.24507/icicel.14.03.289.

[12] Z. Yang *et al.*, “Deep transfer learning for military object recognition under small training set condition,” *Neural Comput Appl*, vol. 31, no. 10, pp. 6469–6478, 2019, doi: 10.1007/s00521-018-3468-3.

[13] Guo Qian, Wang Haipeng, and Xu Feng., “Research Progress on Aircraft Detection and Recognition in SAR Imagery,” *Journal of Radars*, vol. 9, no. 3, pp. 497–813, 2020, doi: http://dx.doi.org/10.12000/JR20020.

[14] Y. Li, Y. Chang, Y. Ye, X. Zou, S. Zhong, and L. Yan, “Category-Aware Aircraft Landmark Detection,” *IEEE Signal Process Lett*, vol. 28, pp. 61–65, 2021, doi: 10.1109/LSP.2020.3045623.

[15] L. Chen, L. Zhou, and J. Liu, “Aircraft recognition from remote sensing images based on machine vision,” *Journal of Information Processing Systems*, vol. 16, no. 4, pp. 795–808, Aug. 2020, doi: 10.3745/JIPS.02.0136.

[16] D. Grosgeorge, M. Arbelot, A. Goupilleau, T. Ceillier, and R. Allioux, “Concurrent Segmentation and Object Detection CNNs for Aircraft Detection and Identification in Satellite Images,” in *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, 2020, pp. 276–279. doi: 10.1109/IGARSS39084.2020.9323338.

[17] Q. Liu, X. Xiang, Y. Wang, Z. Luo, and F. Fang, “Aircraft detection in remote sensing image based on corner clustering and deep learning,” *Eng Appl Artif Intell*, vol. 87, Jan. 2020, doi: 10.1016/j.engappai.2019.103333.

[18] L. Tao, T. Hong, Y. Guo, H. Chen, and J. Zhang, “Drone identification based on CenterNet-TensorRT,” in *2020 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 2020, pp. 1–5. doi: 10.1109/BMSB49480.2020.9379645.

[19] F. Azam, A. Rizvi, W. Z. Khan, M. Y. Aalsalem, H. Yu, and Y. B. Zikria, “Aircraft Classification Based on PCA and Feature Fusion Techniques in Convolutional Neural Network,” *IEEE Access*, vol. 9, pp. 161683–161694, 2021, doi: 10.1109/ACCESS.2021.3132062.

[20] J. Liu, J. Gangwu, X. Wang, B. Xu, and P. Yu, “Feature Extraction and Identification of Military Aircraft Based on Remote Sensing Image,” in *PervasiveHealth: Pervasive Computing Technologies for Healthcare*, Dec. 2020, pp. 128–133. doi: 10.1145/3445815.3445837.

[21] B. Zhao, W. Tang, Y. Pan, Y. Han, and W. Wang, “Aircraft type recognition in remote sensing images: Bilinear discriminative extreme learning machine framework,” *Electronics (Switzerland)*, vol. 10, no. 17, Sep. 2021, doi: 10.3390/electronics10172046.

[22] W. T. Alshaibani *et al.*, “Airplane Type Identification Based on Mask RCNN and Drone Images,” *arXiv.org*, 2021, Accessed: Jan. 23, 2022. [Online]. Available: https://arxiv.org/ftp/arxiv/papers/2108/2108.12811.pdf.

[23] Y. Choi, S. Seol, and I. Choi, “Radar target identification using a DTV-based passive radar in South Korea,” in *2017 Progress in Electromagnetics Research Symposium - Fall (PIERS - FALL)*, 2017, pp. 892–895. doi: 10.1109/PIERS-FALL.2017.8293260.

[24] Headquarters Department of the Army, “TC 3-01.80 Visual Aircraft Recognition Visual Aircraft Recognition,” 2017. [Online]. Available: http://www.apd.army.mil.

[25] P. Svenmarck, L. Luotsinen, M. Nilsson, and J. Schubert, “Possibilities and Challenges for Artificial Intelligence in Military Applications,” in *STO Meeting Proceedings*, 2018.

[26] W. Wang, H. Liu, W. Lin, Y. Chen, and J. A. Yang, “Investigation on Works and Military Applications of Artificial Intelligence,” *IEEE Access*, vol. 8, pp. 131614–131625, 2020, doi: 10.1109/ACCESS.2020.3009840.

[27] S. Anam, “Rainfall prediction using backpropagation algorithm optimized by Broyden-Fletcher-Goldfarb-Shanno algorithm,” in *IOP Conference Series: Materials Science and Engineering*, Aug. 2019, vol. 567, no. 1. doi: 10.1088/1757-899X/567/1/012008.

[28] U. Andayani, R. F. Rahmat, M. F. Syahputra, A. Lubis, and B. Siregar, “Identification of Lung Cancer Using Backpropagation Neural Network,” in *Journal of Physics: Conference Series*, Dec. 2019, vol. 1361, no. 1. doi: 10.1088/1742-6596/1361/1/012060.

[29] U. Andayani *et al.*, “Identification of Retinoblastoma Using Backpropagation Neural Network,” in *Journal of Physics: Conference Series*, Jul. 2019, vol. 1235, no. 1. doi: 10.1088/1742-6596/1235/1/012093.

[30] N. Sevani, I. A. Soenandi, and F. Saputra, “Implementation of backpropagation artificial neural network for early detection of vitamin and mineral deficiency,” in *IOP Conference Series: Materials Science and Engineering*, May 2020, vol. 847, no. 1. doi: 10.1088/1757-899X/847/1/012043.

[31] C. Hayat, I. A. Soenandi, S. Limong, and J. Kurnia, “Modeling of prediction bandwidth density with backpropagation neural network (BPNN) methods,” in *IOP Conference Series: Materials Science and Engineering*, Jul. 2020, vol. 852, no. 1. doi: 10.1088/1757-899X/852/1/012127.

[32] B. Zhao, W. Shi, D. Sun, J. Li, F. Li, and J. Tan, “Extending velocity sensor bandwidth by compensating temperature dependency based on BP neural network,” *IEEE Access*, vol. 7, pp. 154889–154898, 2019, doi: 10.1109/ACCESS.2019.2948261.

[33] Q. Zhang, Y. Guo, and Z. Song, “Dynamic Curve Fitting and BP Neural Network with Feature Extraction for Mobile Specific Emitter Identification,” *IEEE Access*, vol. 9, pp. 33897–33910, 2021, doi: 10.1109/ACCESS.2021.3060794.

[34] A. G. Pertiwi, A. P. Wibawa, and U. Pujianto, “Partus referral classification using backpropagation neural network,” in *Journal of Physics: Conference Series*, Apr. 2019, vol. 1193, no. 1. doi: 10.1088/1742-6596/1193/1/012010.

[35] R. Andrian, B. Hermanto, and R. Kamil, “The Implementation of Backpropagation Artificial Neural Network for Recognition of Batik Lampung Motive,” in *Journal of Physics: Conference Series*, Oct. 2019, vol. 1338, no. 1. doi: 10.1088/1742-6596/1338/1/012062.

[36] X. Zhang *et al.*, “A Digital Signage Audience Classification Model Based on the Huff Model and Backpropagation Neural Network,” *IEEE Access*, vol. 8, pp. 71708–71720, 2020, doi: 10.1109/ACCESS.2020.2987717.

[37] H. Bian *et al.*, “Multiple kinds of pesticides detection based on back-propagation neural network analysis of fluorescence spectra,” *IEEE Photonics J*, vol. 12, no. 2, Apr. 2020, doi: 10.1109/JPHOT.2020.2973653.

[38] X. Shen, Y. Zheng, and R. Zhang, “A Hybrid Forecasting Model for the Velocity of Hybrid Robotic Fish Based on Back-Propagation Neural Network with Genetic Algorithm Optimization,” *IEEE Access*, vol. 8, pp. 111731–111741, 2020, doi: 10.1109/ACCESS.2020.3002928.

[39] Johanes Roisa Prabowo, Rukun Santoso, and Hasbi Yasin, “Implementasi Jaringan Syaraf Tiruan Backpropagation Dengan Algoritma Conjugate Gradient untuk Klasifikasi Kondisi Rumah,” *Jurnal Gaussian*, vol. 9, no. 1, pp. 41–49, 2020, Accessed: Jan. 23, 2022. [Online]. Available: http://ejournal3.undip.ac.id/index.php/gaussian.

[40] A. S. Ahmad and A. D. W. Sumari, “Cognitive artificial intelligence: Brain-inspired intelligent computation in artificial intelligence,” in *Proceedings of Computing Conference 2017*, 2018, vol. 2018-Janua. doi: 10.1109/SAI.2017.8252094.

[41] M. A. Becerra, C. Tobón, A. E. Castro-Ospina, and D. H. Peluffo-Ordóñez, “Information quality assessment for data fusion systems,” *Data (Basel)*, vol. 6, no. 6, Jun. 2021, doi: 10.3390/data6060060.

[42] A. D. W. Sumari and Adang Suwandi Ahmad, “Cognitive Artificial Intelligence: Concept and Applications for Humankind,” in *Intelligent System*, A. S. A. E.-C. Wongchoosuk, Ed. Rijeka: IntechOpen, 2018, pp. 475–502. doi: 10.5772/intechopen.72764.

[43] B. V. Dasarathy, “Sensor fusion potential exploitation-innovative architectures and illustrative applications,” *Proceedings of the IEEE*, vol. 85, no. 1, pp. 24–38, 1997, doi: 10.1109/5.554206.

[44] A. Laksamana, “Sistem Pakar Mendiagnosa Penyakit Kolera Menerapkan Metode Hybrid Case Based,” 2020.

[45] C. G. Hadis, R. Saptono, and A. Azis, “Tourism Recomendation System By Using Positive Negative Apriori and Binary Hamming Distance Algorithm,” *ITSMART: Jurnal Ilmiah Teknologi dan Informasi*, vol. 8, no. 2, pp. 58–64, 2019.

[46] M. D. Samirbhai, S. Chen, and K. S. Low, “A Hamming Distance and Spearman Correlation Based Star Identification Algorithm,” *IEEE Trans Aerosp Electron Syst*, vol. 55, no. 1, pp. 17–30, 2019, doi: 10.1109/TAES.2018.2845198.

[47] X. Li *et al.*, “Image Retrieval Using a Deep Attention-Based Hash,” *IEEE Access*, vol. 8, pp. 142229–142242, 2020, doi: 10.1109/ACCESS.2020.3011102.

[48] M. Ahmad, M. Abdullah, H. Moon, S. J. Yoo, and D. Han, “Image classification based on automatic neural architecture search using binary crow search algorithm,” *IEEE Access*, vol. 8, pp. 189891–189912, 2020, doi: 10.1109/ACCESS.2020.3031599.

[49] K. bin Park and K. S. Chung, “Iterative Pseudo-Soft-Reliability-Based Majority-Logic Decoding for NAND Flash Memory,” *IEEE Access*, vol. 9, pp. 74531–74538, 2021, doi: 10.1109/ACCESS.2021.3079939.

[50] W. Li, H. Liu, Y. Wang, Z. Li, Y. Jia, and G. Gui, “Deep Learning-Based Classification Methods for Remote Sensing Images in Urban

Built-Up Areas," *IEEE Access*, vol. 7, pp. 36274–36284, 2019, doi: 10.1109/ACCESS.2019.2903127.

[51] A. M. Ali, E. Uzundurukan, and A. Kara, "Assessment of Features and Classifiers for Bluetooth RF Fingerprinting," *IEEE Access*, vol. 7, pp. 50524–50535, 2019, doi: 10.1109/ACCESS.2019.2911452.

[52] M. Hasnain, M. F. Pasha, I. Ghani, M. Imran, M. Y. Alzahrani, and R. Budiarto, "Evaluating Trust Prediction and Confusion Matrix Measures for Web Services Ranking," *IEEE Access*, vol. 8, pp. 90847–90861, 2020, doi: 10.1109/ACCESS.2020.2994222.

[53] H. B. Bae, D. Pak, and S. Lee, "Dog nose-print identification using deep neural networks," *IEEE Access*, vol. 9, pp. 49141–49153, 2021, doi: 10.1109/ACCESS.2021.3068517.

[54] M. L. Laia and Y. Setyawan, "Perbandingan Hasil Klasifikasi Curah Hujan Menggunakan Metode SVM dan NBC," *Jurnal Statistika, Industri, dan Komputasi*, vol. 5, no. 2, pp. 51–61, 2020.

[55] R. R. Wahid, F. T. Anggraeni, and B. Nugroho, "Implementasi Metode Extreme Learning Machine untuk Klasifikasi Tumor Otak pada Citra Magnetic Resonance Imaging," in *Seminar Nasional Informatika Bela Negara (SANTIKA)*, 2020, vol. 1, pp. 2747–0563.

[56] W. Castro, J. Oblitas, M. De-La-Torre, C. Cotrina, K. Bazan, and H. Avila-George, "Classification of Cape Gooseberry Fruit According to its Level of Ripeness Using Machine Learning Techniques and Different Color Spaces," *IEEE Access*, vol. 7, pp. 27389–27400, 2019, doi: 10.1109/ACCESS.2019.2898223.

[57] A. U. Haq *et al.*, "Feature Selection Based on L1-Norm Support Vector Machine and Effective Recognition System for Parkinson's Disease Using Voice Recordings," *IEEE Access*, vol. 7, pp. 37718–37734, 2019, doi: 10.1109/ACCESS.2019.2906350.

[58] M. Rangga, A. Nasution, and M. Hayaty, "Perbandingan Akurasi dan Waktu Proses Algoritma K-NN dan SVM dalam Analisis Sentimen Twitter," *Jurnal Informatika*, vol. 6, no. 2, pp. 212–218, 2019, [Online]. Available: http://ejournal.bsi.ac.id/ejurnal/index.php/ji.

[59] C. Qi, J. Diao, and L. Qiu, "On Estimating Model in Feature Selection with Cross-Validation," *IEEE Access*, vol. 7, pp. 33454–33463, 2019, doi: 10.1109/ACCESS.2019.2892062.

[60] V. K. Gupta, A. Gupta, D. Kumar, and A. Sardana, "Prediction of COVID-19 confirmed, death, and cured cases in India using random forest model," *Big Data Mining and Analytics*, vol. 4, no. 2, pp. 116–123, Jun. 2021, doi: 10.26599/BDMA.2020.9020016.

[61] P. A. Pattanaik, M. Mittal, and M. Z. Khan, "Unsupervised Deep Learning CAD Scheme for the Detection of Malaria in Blood Smear Microscopic Images," *IEEE Access*, vol. 8, pp. 94936–94946, 2020, doi: 10.1109/ACCESS.2020.2996022.

[62] N. Li, F. He, W. Ma, R. Wang, and X. Zhang, "Wind Power Prediction of Kernel Extreme Learning Machine Based on Differential Evolution Algorithm and Cross Validation Algorithm," *IEEE Access*, vol. 8, pp. 68874–68882, 2020, doi: 10.1109/ACCESS.2020.2985381.

[63] E. T. Institute, "Aircraft Performance Database," *EUROCONTROL Training Institute*, Mar. 04, 2021. https://contentzone.eurocontrol.int/aircraftperformance/default.aspx? (accessed Mar. 04, 2021).

[64] A. D. W. Sumari, A. I. Wuryandari, M. Darusman, and N. I. Utama, "The Performance of Supervised and Unsupervised Neural Networks in Performing Aircraft Identification Tasks," in *Seminar Radar Nasional III*, 2009, pp. 16–22.

[65] E. F. Nakamura, A. A. F. Loureiro, and A. C. Frery, "Information fusion for wireless sensor networks: Methods, models, and classifications," *ACM Comput Surv*, vol. 39, no. 3, Sep. 2007, doi: 10.1145/1267070.1267073.