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A Novel Approach for Recognition and Identification of Low-Level Flight Military Aircraft using Naive Bayes Classifier and Information Fusion

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ABSTRACT

A problem that has been faced by the Radar is if the aircraft flies at low level or near to the surface so its coming in the aerial-surveillance airspace cannot be detected and endangers the air sovereignty. The aircraft can be recognized and identified by carrying out a technique called Visual Aircraft Recognition (VACR) using a binocular. This technique requires military personnel that has capability carrying out the air surveillance from the ground. Surveillance is a time-consuming and tiring task so it can cause fatigue and impact to the results of the recognition and identification. To cope with this problem, we have designed and implemented a novel recognition and identification method using the combination of Naive Bayes Classifier (NBC) and information fusion. By using a dataset that consists of 45 military aircrafts, 35 civilian aircrafts, 40 military helicopters, and 35 civilian helicopters with 80:20 dataset distribution for the training scheme and the validation one, we obtained the recognition accuracy of 87.1%. We also found that the recognition and identification process can be speeded up 1.2 seconds when using information fusion.

I. Introduction

Guarding the national airspace is the primary task of the National Air Defense Command (NADC). For this carrying out this task, the Armed Forces deploys the Radar systems at some strategic locations in order to detect, recognize, and identify the incoming aircrafts from any direction to the national airspace. Even though, the Radar systems are designed to able to detect high-speed aircrafts at a long distance, but they can be tricked if the aircrafts fly at low level altitude or it is said as flying nap-to-the-earth [1], which is out-of-the Radar coverage. This kind of flight can occur anywhere and anytime that can endanger the air sovereignty if such aircrafts are not detected, recognized, and identified at the right time. Therefore, a ground-to-air surveillance to assist the Radar systems. This surveillance can be carried out by the competent Armed Forces personnel who are already given a Visual Aircraft Recognition (VACR) [2] training. This task is called as ground-to-air surveillance and it is performed by using binoculars to assist a faraway observation to the incoming or passing aircrafts as depicted in Fig. 1.

Ground-to-air surveillance is a time-consuming and tiring task while on the other hand, keeping in mind so many types of military aircrafts will give another load that can bring the personnel into fatigue situation and cause a mistake recognition and identification. Aircraft is any machine that can fly because of having a lift caused by the air. It is divided into two categories namely, airplane which is called fixed wing aircraft, and helicopter which is common called as rotary wing aircraft. In the utilization, they are also categorized into more detail that is, military airplane and civilian one, and military helicopter and civilian one. We use military aircraft terminology to cover all military aircraft categories whether it is airplane or helicopter. Each aircraft category has its own characteristics that differentiate its appearance one to another. Even though in general most of the characteristics are the same, but how the characteristics put on the aircraft will affect to the type of the aircraft. Therefore, remembering all those characteristics along with remembering the type of the aircrafts that posse them is a challenge knowing that the types of aircraft are more various with newer characteristics.

Fig. 1. A soldier is performing ground-to-air surveillance to recognize an incoming aircraft.

Motivated by the desire to enhance the Armed Forces' NADC in recognizing and identifying low level flight aircrafts that may be hostile, we propose a novel approach for recognizing and identifying such objects by using the combination of Naive Bayes Classifier (NBC) as the recognizer and information fusion as a means to speed up the process. It is realized that techniques used by defense and military sectors mostly are classified and hard to find through public databases. The-state-of-the-art for recognizing and identifying low level flying objects are very little and very rare. Researches on the identification of aircraft by machine learning techniques were conducted to the combination of the object speed and its Radar Cross Section using Adaptive Resonance Theory 1 (ART 1) [3], ART 2 [4], and Back Propagation Network (BPN) [5] as well as the comparison of their performances [6]. The latest state-of-the-art is by utilizing signal processing approach called Spectrum Zoom Processing. But none of those techniques is the same to ours knowing that VACR was just updated in 2017 with some additions to aircraft types including their characteristics [2].

II. Literature Review

A. Visual Aircraft Recognition (VACR)

VACR is a technique to recognize an aircraft from its appearance using a long-distance visual observation tool such as binocular. Differ from the Radar systems, VACR is carried out a trained Armed Forces personnel who is tasked to perform ground-to-air surveillance. The objective of VACR is to train the Armed Forces personnel especially the Army soldiers to be able to differentiate the incoming aircraft in order to not only detect its entering to the sovereignty airspace, but also to recognize and identify its type and name. From the aircraft recognition and identification that is being carried out, he or she can predict that such incoming aircraft is friend, foe, or neutral [2]. VACR was becoming important when the world entered the Second World War (WW II) when the aircrafts were one of the means to defeat the other countries' Armed Forces. In that time, the attack from above was a way to destroy adversary's strategic facilities in a quick time and it was done by various types of aircrafts. Therefore, it was needed a means to recognize the aircrafts in order to avoid friendly fire to own aircrafts [7].

There are two levels of recognition, namely general recognition and detail recognition. In the case of VACR, recognition is to recognize types of objects based on its quantitative features as well as the primary characteristics of the object [8]. General recognition is able to recognize an aircraft based on its class, that is fixed wing and rotary wing, while the detail recognition is able to recognize an aircraft based in its type, that is military, civilian, and helicopter [9]. As the name says in VACR, recognition is the primary skill for ground-based air defense systems personnel who operate the weapon systems such as anti-air artillery (AAA) or ground-to-air missile. Therefore, the skill of recognizing the type and the name of the entering aircrafts correctly is a must. On the other hand, visual recognition whether by eyes or assisted by a binocular is a complex skill with a certain level of skill and precedency that can be obtained through a series of training [10].

There were three methods introduced to train the personnel so as to be able to recognize and identify an aircraft by using its characteristics that have to committed into memo, namely Wing, Engine, Fuselage, Tail (WEFT) method, Renshaw System, and Sargeant System [7]. WEFT then was adopted by the US Navy and US Army Air Corps in 1941. This method has been used by the US Army until now with the publication of its latest VACR dated 2017 [2]. Some images to show WEFT are depicted in Fig. 2, while a simple explanation of those four primary aircraft characteristics is as follows.

- Wing is a part of the aircraft that is used to produce the lift. It is the place where some control surfaces are installed such as ailerons and elevators, and also the air brakes.
- Engine is a part of the aircraft that is used to produce thrust so it can roll on the runway and take off to the air.
- Fuselage is the main body of the aircraft where the air crews as well as the passengers sit.
- Tail is the part if the aircraft where some control surfaces also installed to assist the ones installed in the wing. They include rudder and other assisting subsystem. Some aircrafts have engines installed in this section.

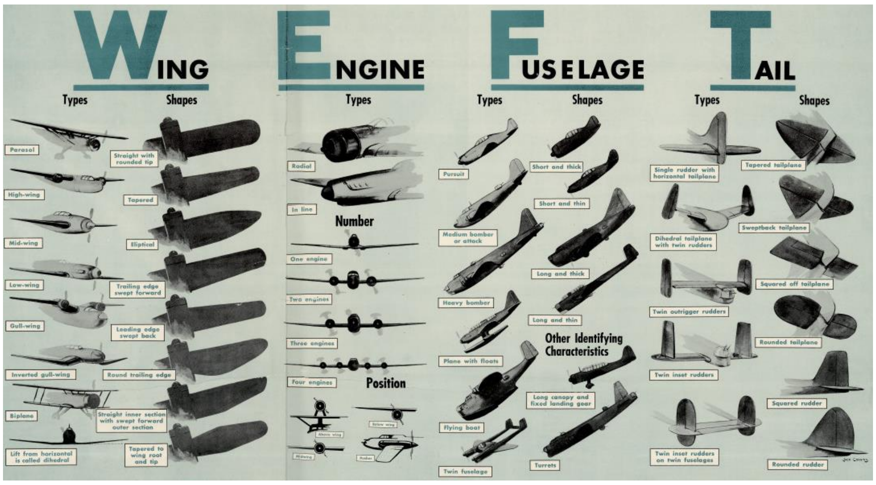

Fig. 2. Images of WEFT along with their subcharacteristics [11].

B. *Naive Bayes Classifier* (NBC)

In its simple view, Naive Bayes Classifier (NBC) is probabilistic engine that brings all characteristics of Bayes formulation ideated by Rev. Thomas Bayes more than one century ago, that is called Bayes theorem. This method is common being used to calculate the probability of a chance based on the known attributes or characteristics as a means to determine the most accurate class refereeing to the highest probability value [12]. In its simple form, this theory is shown in (1).

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)} \quad (1)$$

where:

- y and X are events. The first one is said as the hypothesis of the data X which is a specific class, while the last one is the data with known class.

- $P(y|X)$ is the probability hypothesis y is class X, and said as a posteriori probability.
- $P(X|y)$ is the probability class X known the existence of hypothesis y, and said as a priori probability
- $P(y)$ is the probability of hypothesis y exists.
- $P(X)$ is the probability of class X exists.

For recognition, which is a classification task, NBC can be extended as shown in (2).

$$P(y|x_1, \dots, x_n) = \frac{P(x_1, \dots, x_n|y)P(y)}{P(x_1, \dots, x_n)} \tag{2}$$

- y is the positive class, x_1 is the first feature for the instance, and n is the number of features.
- $P(x_1, \dots, x_n)$ is constant for all inputs that can be omitted. The probability of observing a particular feature in the training set does not vary for different test instances.
- NBC performs the classification by using two terms, that is the prior class probability, $P(y)$, and the conditional probability, $P(x_1, \dots, x_n|y)$ called as Maximum a Posteriori (MAP) as shown in (3), while the estimated or predicted class is obtained by using (4).

$$\begin{aligned} P(y|x_1, \dots, x_n) &\propto P(y)P(x_1|y)P(x_2|y) \dots . P(x_n|y) \\ P(y|x_1, \dots, x_n) &\propto P(y)\prod_{i=1}^{n} P(x_i|y) \end{aligned} \tag{3}$$

$$y = argmax_y P(y)\prod_{i=1}^{n} P(x_i|y) \tag{4}$$

C. Information Fusion

A process to produce a comprehensive information from a collection of data or information is called as information fusion. This concept came from the observation to the generation of knowledge within the human brain. The knowledge generation is started from the sensing and perceiving of the environment, especially a specific phenomenon, carried out by the sensory organs. The sensing and perceiving can be done by at least two sensory organs in order that the knowledge generation mechanism can work. If only one sensory organ, say sensor A, that senses and perceives an information, the generated knowledge may not be able to know the phenomenon. Therefore, another sensor, say sensor B, will be required to do same activities to get more information of it. The information from the two sensors, sensor A dan sensor B, is then combined and extracted to obtain the knowledge. This mechanism is called as information fusion. The ultimate result of information fusion is new knowledge [13].

In our case, the inputs to the system are the results of the soldier ground-to-air surveillance as depicted in Fig. 1. During the observation, the observing soldier or simply, the observer will be observing the observable characteristics that he can see through the binoculars. For each observable characteristic, he would tell his fellow soldier to enter the characteristic into the system. Once all observable characteristics are already entered, the system would output the prediction the class and also the type of the observed aircraft. This prediction is then reported to the higher command for the decision. The mechanism that is occurred within the system emulates what may occur within the human brain as illustrated in Fig. 3. It can be seen that the inputs in the form of the aircraft characteristics will be fused to generate knowledge that makes the system is able to recognize and identify the aircraft.

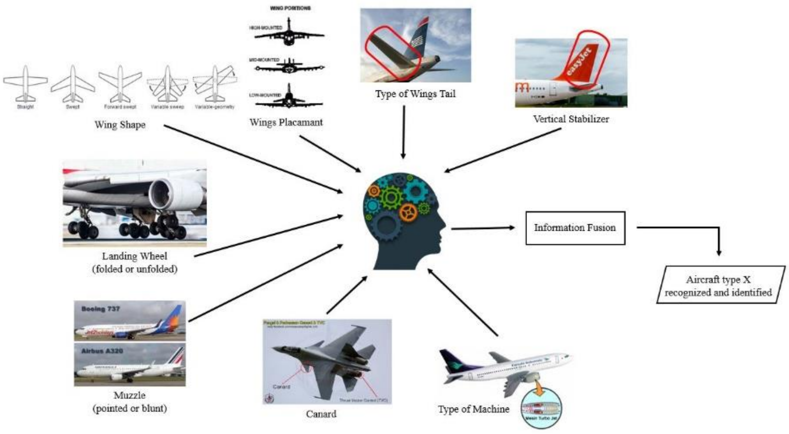

Fig. 3. Illustrated mechanism of information fusion within the human brain in recognizing and identifying an aircraft.

There are various techniques for performing the information fusion. In our research, we use Dasarathy Model is represented by 4x4 matrix that maps the relationship amongst Data (DA), Features (FE), Objects (DE), and Relation (RL). As example, DAI-DAO means Data as Input with Output in from of Data to represent Signal Detection while DAI-FEO means Data as Input and Feature as the Output, and so on. In our research, we use two modes as follows.

- DAI-FEO that is applied when performing feature extraction from the data in the form of aircraft characteristics. The mechanism carried by converting each characteristic into its corresponding binary number representation. We use 16 bits in order to reduce the possibility of the same information fusion results. From primary WEFT characteristics, we extended into deeper ones and made them into nine characteristics which two of them are additional ones in order to produce better recognition and identification. All aircraft characteristics taken from WEFT and two additional ones are shown in Table I.

TABLE I. AIRCRAFT CHARACTERISTICS.

Characteristic	**Specific Parts**
Wing Type	Rotary Wings
	Fixed Wings
Wing Placement	High Wings
	Mid Wings
	Low Wings
	Don't Have Wing Placement
Wing Direction	Straight Wings
	Sweptback Wings
	Forward Swept Wings
	Delta Wings
	Rotor Wings
	Don't Have Wing Direction
Engine Type	Piston
	Turbo Jet
	Turbo Prop
	Turbo Fan
	Turbo Shaft
Engine Placement	On The Wing
	Behind Fuselage
	Above Fuselage
	Behind Cabin
	Above Cabin

Characteristic	**Specific Parts**
	In Fuselage
	Front Fuselage
	Close to the Fuselage
Fuselage Type	Subsonic
	Supersonic
	High-Capacity Subsonic
	High-maneuverability Supersonic
	Flying Boat
	Hypersonic
	Dragonfly
Tail Type	Conventional Tail
	Twin Tail
	T-Tail
	Cruciform Tail
	H-Tail
	V-Tail
	No Tail (double main rotor)
	Tail Rotor
	Don’t have Tail
Weaponry	Have Weaponry
	Don't Have Weaponry
Color	Stripes
	No Stripes

- FEI-FEO that is applied when performing information fusion to produce new 16-bit binary number that represents all fused binary numbers. All 9 characteristics are fused to obtain single binary number by using X-OR function. This mechanism is shown in (5).

$$Fused\_characteristic \ = XOR_{i=1}^{n}(characteristic_i) \tag{5}$$

III. Results and Discussion

A. System Architecture

Before proceeding to computation, we have to apprehend how the system works. Our system is not completely because we need human in the loop as agents that inform the observation results to the system. Referring to Fig. 4, Radar can only recognize the incoming aircraft if it is in its signal coverage and detected. It can also identify if it turns off its identification code. A low-level flight incoming aircraft is intended to avoid Radar detection. Therefore, a ground-to-air surveillance has to be carried out to detect, recognize, and identify it. The visual data resulted from the observation is entered in the system by the soldier and once it is completed, the system will do the rest to deliver the results in form of the recognized category along with its identified type.

B. The Dataset

As NBC is categorized as statistical-based machine learning technique, then in order that the system is able to recognize and identify an incoming aircraft’s characteristics entered by the soldier, it has to learn various types of aircraft as well as their characteristics. We use a dataset that contains 155 types of aircrafts consisting of 45 military aircrafts, 35 civilian ones, 40 military helicopters, and 35 civilian ones. The dataset was taken from various references such as [14] [15] [16] [17] [18]. We sorted out the characteristics of each aircraft and put it in the dataset and use them as the inputs where each of them has to be entered one by one with careful to reduce the error in the final result.

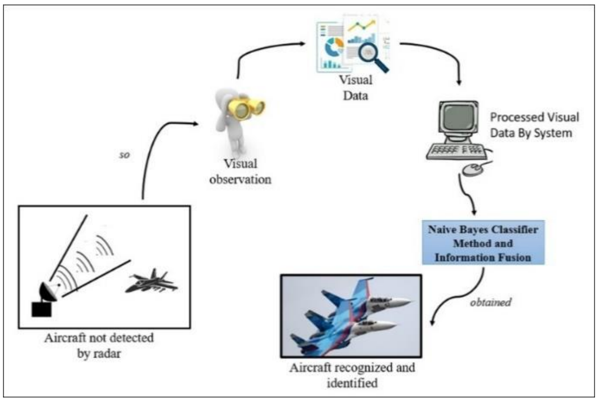

Fig. 4. The system architecture.

After all characteristics inputted into the system, then DAI-FEO and FEO-FEI will do their jobs as presented in Table II with an example the extracted features from CN-235 aircraft along with its fused information. The aircraft is depicted in Fig. 5 viewed from various perspectives, namely, side view, top view, and front view. Those views give insights regarding the aircraft characteristics as stated in WEFT as well as the additional characteristics.

Fig. 5. Various views of CN-235 aircraft [19] and its military version with stripes [20].

TABLE II. EXTRACTED FEATURES FOR CN-235 AIRCRAFT WITH ITS FUSED INFORMATION.

No.	Characte-ristics	Specific Parts	Features (DAI-FEO)	Fused Information (X-OR-ed FEI-FEO)
1.	Wing Type	Fixed Wings	0000000000000010	
2.	Wing Placement	High Wings	0000000000000100	
3.	Wing Direction	Sweptback Wings	0000100000000000	
4.	Engine Type	TurboProp	0001000000001000	
5.	Engine Placement	On The Wing	0010010010000100	1011100110001011
6.	Fuselage Type	Flying Boat	0000000000100001	
7.	Tail Type	Conventional Tail	0000000100010000	
8.	Weaponry	Don't Have Weaponry	1000010001000000	
9.	Color	No Stripes	0000000001110000	

C. The Computation Mechanism

The computation to the fused information was carried out by following the procedures as follows.

- Calculate the probability of each aircraft type in the dataset.
- Calculate the number of aircrafts that have the same fused information value. It cannot be avoided because some aircrafts have identic characteristics.

- Calculate the a priori probability, that is the recognition of a certain aircraft by knowing a certain fused information.
- Calculate the posteriori priori probability, that is the combination of the a priori probability with the probability of each aircraft type in the dataset.

D. The Computation Results

As normally done in machine learning, we split the dataset into two folds, that is, 80% or 124 data for training scheme and 20% or 31 data for test or validation data. We also coded each class of aircraft as follows: Class 0 is for military helicopter, Class 1 is for civilian helicopter, Class 2 is for military aircraft, and Class 3 is for civilian aircraft.

We also did k-fold validation test to ensure the robustness of the model. After the model passed the training scheme, we validated it with 31 aircraft data and the results are shown in some confusion matrices that show how to obtain the total values for True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) for multi-class classification. In Table IV shows the confusion matrix for all validation results, the row-columns with blue color for each class show the TP value for each class. From the table, it is easy to see that the recognition accuracy of the system is 87,1% and can be obtained as follows.

The complete results of the validation scheme are presented in Table V which include Recall, Precision, and F-1 Score. The robustness of the model was also validated with k-fold technique and the results are shown in Table VI. As previously stated, the use of information fusion is to speed up the recognition and identification. To prove our hypothesis, we had tested the system with the results as shown in Table VII.

TABLE III. THE CONFUSION MATRIX OF THE VALIDATION RESULTS.

	0	**1**	**2**	**3**
0	7	0	0	0
1	0	7	0	1
2	0	0	7	0
3	0	0	3	6

$$\begin{aligned} Accuracy &= \frac{Total\ TP\ (The\ Sum\ of\ TPs\ of\ All\ Classes)}{Total\ Number\ of\ Validation\ Data} \\ &= \frac{7+7+7+6}{31} \\ &= 0{,}871\ or\ 87{,}1\% \end{aligned}$$

TABLE IV. THE COMPLETE RESULTS OF THE VALIDATION SCHEME.

Class	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Class 0: Military Helicopter	0.871	1	1	0.87
Class 1: Civilian Helicopter		1	0.874	0,87
Class 2: Military Aircraft		0.7	1	0.87
Class 3: Civilian Aircraft		0.857	0.667	0.87
Average	**0.871**	**0.889**	**0.885**	**0.87**

TABLE V. THE RESULTS OF K-FOLD VALIDATION.

k-Fold Cross Validation		**80:20 Scheme Accuracy**
k	**Average Accuracy**	
3	89.61%	87.1%
5	87.1%	
10	76%	

TABLE VI. THE RESULTS OF SPEED PROCESSING COMPARISON.

With Fused Information	Without Fused Information	Time Difference
0.54 seconds	1.74 seconds	1.2 seconds

E. Validating the System with A Brand-New Aircraft Data

In order to validate our system, we provided a brand-new aircraft data that is not in the dataset whether in the training scheme or in the validation one. The aircraft is A-10 Thunderbolt, a subsonic ground-to-air attack type aircraft as depicted in Fig. 6, with the characteristics as shown in Table VIII. We entered these characteristics carefully into the system that we have developed. After doing the processing, the system delivered the results that the aircraft that has the inputted characteristics is recognized as military aircraft. It is also identified as five types of aircraft, namely Chengdu J-7, F-16 Fighting Falcon, JF-17 Thunder, Yakovlev Yak-130, and Hongdu JL-15, that are predicted as the most similar to A-10 Thunderbolt. The predicted types of aircraft are shown in Fig. 7, while the process of recognition and identification is presented in Fig. 8.

TABLE VII. THE CHARACTERISTICS OF A-10 THUNDERBOLT AIRCRAFT.

Characteristics	Specific Parts	Features (DAI-FEO)	Fused Information (X-OR-ed FEI-FEO
Wing Type	Fixed Wings	0000000000000010	
Wing Placement	Mid Wings	0000000000001000	
Wing Direction	Sweptback Wings	0000100000000000	
Engine Type	Turbofan	0000100000010000	
Engine Placement	Behind Fuselage	0001001100001000	**1010000010010010**
Fuselage Type	Subsonic	0000001000010000	
Tail Type	Conventional Tail	0000010000100100	
Weaponry	Have a Weapon	1000100010000000	
Color	Stripes	0011100000000000	

Fig. 6. A-10 Thunderbolt ground-to-air attack aircraft [21].

(a) Chengdu J-7 [22].

(b) F-16 Fighting Falcon [23].

(c) JF-17 Thunder [24].

(d) Yak-130 [25].

(e) Hongdu JL-15 [26].

Fig. 7. Five types of predicted aircraft based on the characteristics entered to the system.

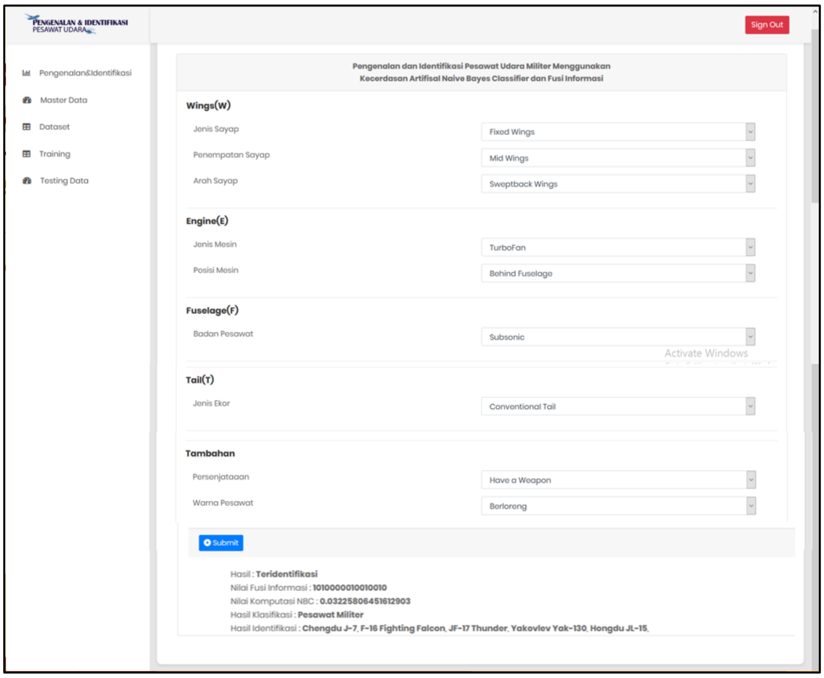

Fig. 8.The recognition and identification of A-10 Thunderbolt aircraft with five different types of aircraft that are the most similar. The application is developed with dual-language especially for WEFT terminologies.

F. Discussion

Based on the results have been delivered at the previous section, the hypotheses we raised in are proven correct as follows.

- Aircraft recognition and identification can be carried out by combining machine learning NBC and information fusion. NBC acts as the aircraft class recognizer which are divided into four classes, namely military as well as civilian helicopter, and military as well as civilian aircraft, while the information fusion is used to speed up the recognition process and its fused information is used as the means to identify the type of the recognized aircraft. The fuse information is a sequence of binary code that will match the entered characteristics with the fused information of the aircrafts in the NBC knowledge base.
- With 80:20 dataset split for the training scheme and the validation one, the system is able to achieve 0.871 or 87.1% recognition accuracy. On the other hand, the system is able to recognize and identify a brand-new aircraft to the most similar aircrafts that have the similar characteristics. A-10 Thunderbolt is a special aircraft and none of aircraft in the world has identical characteristics to it. Therefore, it is a hard challenge to recognize and identify this kind aircraft. The ability of the system to recognize and identify it as five types of aircraft from three different countries show that it works well. At least, if the real situation occurs, the recognition and identification results are an alert regarding the incoming aircraft that can be hostile, and this is also the basis for NADC to dispatch the equal-capability aircrafts to intercept it.
- We also found that the use of information fusion technique has able to speed up the recognition and identification system by 1.2 seconds over that of without information fusion. In the real situation, speed is matter because the recognition and identification races against the time as the fighter aircraft flies faster than other aircrafts and helicopters. The speed of reporting the recognition and identification to NADC will affect to the speed in dispatching the aircrafts to intercept the incoming aircraft.
- The robustness of the system is also proven through k-fold validation where the identical accuracy was obtained at $k = 5$, that is 87.1%. This is very reasonable because when $k = 5$ the amount of data in each fold is even, that is 31 data, while when $k = 3$ and $k = 10$ the amount

of data in each fold is not even and it caused imbalanced amount of data during validation. This situation can be said as lack of density that impacts to the occurrences of FN or FP to determine the accuracy [27].

IV. Concluding Remarks

We have discussed the results of our research on the recognition and identification of military aircraft by utilizing machine learning NBC combined with information fusion technique. In this final section, we deliver the conclusion as well as our further works to refine the system so it has more capabilities.

A. *Conclusion*

- The combination of machine learning NBC and information fusion can be alternative to assist the soldier in the field when performing ground-to-air surveillance aginst low-level flight incoming aircrafts, and reduce the load of memorizing so many aircrafts types with their characteristics from various countries.
- Information fusion is proven able to speed up the recognition and identification of aircraft whether military or civilian airplane and helicopter.
- The k-fold validation has proven the robustness of the system with the accuracy of 87.1%. It also achieves 88.9% for Precision, 88.5% for Recall, and 87.6% for F-1 Score.

B. *Further Works*

- We have noted other specific characteristics of aircrafts, such as the number and the shape of engine that can become differentiating characteristics for specific aircrafts. We will add these characteristics to increase the system accuracy.
- We also have considered to enhance the system in two ways. The first one is to add voice-to-text transducer to replace the system operator, and the second one is to use long-range camera that is equal to the binoculars distance to capture the incoming aircraft in form of image or video. The second additional subsystem is connected directly to the main system so the recognition and identification can be carried out more quickly.

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