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AN INTELLIGENT AIRCRAFT IDENTIFICATION SYSTEM FOR EMERGENCY LANDING SCHEDULING USING BAYESIAN REGULARIZED NEURAL NETWORK

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ABSTRACT

Flight plans are manually created from the radar controller's position and flight data processing manually inputted from the submitted flight plan for each aircraft. This manual system is prone to errors while handling emergency landing requests. This necessitates the need to have automated and reliable control systems that can support fast system identification. This paper presents a Bayesian Regularized Neural Network (BRNN) model for aircraft identification to be inculcated into the existing aircraft identification and squawk code allocation system (based on Aircraft Classification Number) at the secondary surveillance radar end where an Air Traffic Controller can use it for identifying and scheduling of aircrafts for emergency landing at the aerodrome. The Bayesian regularized neural network solution presented in this work automates the existing manual flight data processing thereby improving its speed and accuracy. Flight tests data obtained from the Nigerian Airspace Management Agency (NAMA), Lagos database were used to form samples for training of the neural network. The BRNN model was evaluated using neural network fitting application in MATLAB (R2021a). The results obtained proved effectiveness of the presented BRNN solution to identify the air traffic control codes for aircraft identification with an accuracy of 98.79% at a speed of 2 seconds. Hence, it can be used for identification of aircrafts for safe emergency landing scheduling and utilization of the aerodrome pavements.

Keywords: Bayesian Regularized Neural Network, Aircraft Classification Number, Pavement Classification Number, Radar.

INTRODUCTION

Radar can be distinguished into two main categories: primary radar and secondary radar. Primary radar interrogator sends a pulse, which is reflected by a target (aircraft). The sensor on the ground then detects this echo. With this system, the aircraft's position is detected, but not its identity. Secondary radar is not actually true radar like the primary radar. A radar transmitter on the ground sends a pulse (interrogation) to an aircraft, the on-board transponder then replies with the identity of the aircraft and its altitude. Secondary Surveillance Radar (SSR) interrogator produces two different kinds of interrogations. One asks for aircraft identification and the other for altitude. These two interrogations have to be different, and must be recognized by the aircraft's transponder. Interrogations are divided into groups, called "modes". Most aircrafts are now equipped with a mode C transponder that replies with identity and altitude. The transponder transmits a 4-digit code as a reply to an interrogation by a radar station. The 4 digit code is called a squawk code. Each digit of a squawk varies from "0" to "7" only (octal numeral system). By combining 4 numbers from "0" till "7" ("0000" - "7777"), four thousand and ninety six (4,096) different squawk codes are available. SSR identifies aircrafts according to their squawk code.

The Aircraft Classification Number (ACN)

The Aircraft Classification Number (ACN) is a single unique number expressing the relative effect of an aircraft on a pavement for a specified sub-grade strength specifying a particular pavement thickness. It consists of a number on a continuous scale, ranging from zero on the lower end and with no upper limit, that is computed between two pavement types (rigid or flexible), and the sub-grade support strength category. ACN values for civil aircraft have been published in International Civil Aviation Organization's (ICAO) Aerodrome Design Manual **[18]** and in Federal Aviation Authority (FAA) Advisory Circular 150/5335-5 **[15]**. The ACN is twice the derived single-wheel load expressed in thousands of kilograms, with single-wheel tyre pressure standardized at 1.25 mega-pascals (=0.09 ton/ft^2). Additionally, the derived single-wheel load is a function of the sub-grade strength. The ACN of an airplane is a function of not only its weight but also the design parameters of its landing gear such as the distances between the wheels of a multiple-wheel landing gear assembly. The pavement's strength is denoted by its Pavement Classification Number (PCN). The load exerted on a pavement by the landing gear of an airplane is denoted as its ACN, or Airplane Classification Number. The ACN is not permitted to exceed the PCN of the runway to be used, in order to prolong pavement life and prevent possible pavement and aircraft damage. The ACN is defined for only four sub-grade categories – high, medium, low, and ultra low. The International Civil Aviation Organization (ICAO) system for civil airport pavements involves comparison of an airport's Pavement Classification Number (PCN) with an Aircraft Classification Number (ACN). The ACN-PCN system of rating airport pavements is designated by the ICAO as the only approved method for reporting strength **[19]**. According to this world-wide ICAO standard, aircraft can safely operate on a pavement if their ACN is less than or equal to the pavement load bearing capacity or PCN. An aircraft having an ACN equal to or less than the PCN can operate without weight restrictions on a pavement. The ACN-PCN method only deals with aircraft weighting in excess of 5,700 kg (12,566 lb) as the airports with pavement for smaller size aircraft need only report the maximum allowable mass and the maximum allowable tyre pressure if applicable**.** The ACN-PCN system ensures that both aircraft and pavement can be utilised to their maximum extent without detrimental effects.

Problem Identification

Flight data processing for aircraft identification are manually done at emergency requests and is prone to delays and errors. This paper provided a Bayesian Regularized Neural Network based intelligent aircraft identification system for air traffic controllers to identify aircrafts for emergency landing scheduling to ensure its specification does not exceed the pavement specification for the aerodrome to avoid detrimental effect on the aircraft and the pavement as well as other aircrafts in the aerodrome.

Bayesian Regularized Neural Network (BRNN)

The Bayesian Regularization is a training algorithm that updates the weights and bias values according to Levenberg-Marquardt optimization and minimizes errors associated with backpropagation algorithms and the likelihood of over fitting the training data. It minimizes a combination of squared errors and weights, and then determines the correct combination to produce a network that generalizes well **[5]**. Regularization is a traditional way of dealing with the negative effect of large weights. The idea of regularization is to make the network response smoother through the modification in the objective function by adding a penalty term that consists of the squares of network weights. This additional term favours small values of weights and decreases the tendency of a model to overfit noise in the training data **[12]**. The aim of training is to reduce the sum of squared error, E_d. The training objective function is:

$$F = E_d = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 \qquad (1)$$

The Bayesian Regularization approach modifies the objective function. The objective function in equation (1) is expanded with the addition of a term, E_w which is the sum of squares of the network weights, hence the objective function is expressed thus:

$$F = \beta E_d + \alpha E_w \qquad (2)$$

where α and β are the objective function parameters which are to be optimized and are defined using the Bayes' rule **[6]**. Bayesian Regularized neural networks are more robust than standard backpropagation networks. The Bayesian regularization training algorithm compared to standard backpropagation has higher level of functionality and the validation process is not necessary. The function "trainbr" that performs Bayesian regularization disables validation stops by default. This is because validation is usually used as a form of regularization, but "trainbr" has its own form of validation built into the algorithm. Hence "trainbr" does not require a validation dataset. Over-training the network using the trainer is difficult as a result of its procedures which provide a targeted Bayesian criterion for training to stop. Over-fitting the network is also difficult as the trainer calculates and trains several numbers of valid network parameters/weights, and eliminating those that are invalid **[3]**.

REVIEW OF RELATED WORKS

It has been shown by Roudbari and Saghafi **[9]** that Artificial Neural Network (ANN) has enough potential for system identification of aircraft dynamics that can be used for various purposes. ANN was used to model the dynamic behaviour of the highly maneuverable aircraft. The work was limited to identification of the aircrafts nonlinear dynamics and could not give actual identification of the aircraft type. Roopa *et al* **[8]**, used neural networks for fighter aircraft recognition for military applications. This work had a drawback of complexity in correctly identifying the unknown aircraft irrespective of its orientations. Also the accuracy of recognition (91%) is not sufficiently high enough for the intended purpose. In the work by Xu *et al* **[14]**, an end-to-end Fully Convolutional Network (FCN) for aircraft detection from remote sensing images was presented. The work proved efficient in detection of aircraft but did not cover identification of the aircraft. Binarized Normed Gradients (BING) technique and Convolutional Neural Network was used by Wu *et al* **[13]** for fast detection of aircrafts in satellite images. This method yielded a good performance on aircraft detection but could not identify the aircraft. Wang *et al* **[11]** proposed the Aircraft Targets Region Proposal Network (ATRPN) – Regional Convolutional Neural Network (R-CNN) aircraft target detection method for remote sensing image based on the Faster R-CNN target detection algorithm. This work did not consider aircraft identification. A collocation-based output-error method for parameter estimation for aircraft system identification was presented by Dutra **[4]**. Notable limitations of the output-error method are that it requires ad hoc modifications for applications to unstable systems and it is an iterative method which is particularly sensitive to the initial guess. Raj and Gnana **[7]** simulated an Air Traffic Control system for both landing and taking-off aircrafts based on availability of runways, safety criterions, efficient operations management and environmental parameters. It did not cover identification of the aircrafts. In the work by Al-Emadi and Al-Senaid **[2]**, a Convolutional Neural Network (CNN) technique was used for drone detection and classification using Radio Frequency (RF) signals emitted during the live communication session between the drone and its controller. The level of accuracy for the drone identification is low (88.4%). Al-Emadi *et al* **[1]**, developed drone detection and identification methods using Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Convolutional Recurrent Neural Network (CRNN). The level of accuracy of the drone identification results are not high enough (57.16%, 92.94% and 92.22% respectively). In the work by Shijith *et al* **[10]**, image processing using Convolutional Neural Network (CNN) was used for detecting the presence of UAVs that breach the perimeter and measures taken to disable it. The work was limited by inefficient controller board (Raspberry pi) which takes more time for identification of the drones.

In the course of review of related works for this study, no solution was found that used the Bayesian Regularized Neural Network (BRNN) for identification of aircrafts based on the

Aircraft Classification Number (ACN) and individual data features of the aircraft. The related works centred more on target detection rather than actual aircraft identification. Much work have not been done in the area of aircraft identification and the levels of identification accuracy reported in the reviewed literature are not high enough considering the severity of the problem. This work tried to fill this research gaps by using the Bayesian Regularized Neural Network to develop an aircraft identification system based on Aircraft Classification Number (ACN) to be inculcated into the existing aircraft identification and squawk code allocation system.

METHODOLOGY

In this study, an interactive environment for modelling, analyzing, and evaluating a wide variety of dynamic systems provided by Mathworks through Neural Network Fitting application was used. Neural Network Fitting application is a graphical user interface (GUI) designed for solving data-fitting problems using a two-layer feed-forward network. It helps in selecting and dividing data for training, testing and validation, as well as defining the network architecture and training the network. It also generates MATLAB scripts which can be used to reproduce the results or customize the training process **[20]**. For this research Neural Network Fitting application (**nftool**) in MATLAB R2021a was used.

Data Set for the BRNN

The dataset used in this work was obtained from the Aircraft Classification Number database of the Nigeria Airspace Management Agency (NAMA), Lagos which is shown in table 2. The aircraft identification parameter values which are connected to the squawk code were presented to the network as input and target variables. The input (p) represents Tyre Pressure (MPa), Flexible Pavement Sub-Grades (CBR%) and Rigid Pavement Subgrades k(MPa/m^3) which formed a 276 row by 9 column matrix representing static data; 276 samples of 9 elements. The target (t) represents Weight Maximum (kN) of the aircraft, which formed a 276 row by 1 column matrix representing static data; 276 samples of 1 element.

Table 1: The Data Set Variables

#	Input Variables	#	Target Output Variable
X_1	Tyre Pressure (MPa)	Y	Weight Maximum (kN)
X_2	Flexible Pavement Sub-grade (CBR%) – High		

X_3	Flexible Pavement Sub-grade (CBR%) – Medium		
X_4	Flexible Pavement Sub-grade (CBR%) – Low		
X_5	Flexible Pavement Sub-grade (CBR%) - Ultra low		
X_6	Rigid Pavement Sub-grade [k(MPa/m^3)] – High		
X_7	Rigid Pavement Sub-grade [k(MPa/m^3)] – Medium		
X_8	Rigid Pavement Sub-grade [k(MPa/m^3)] – Low		
X_9	Rigid Pavement Sub-grade [k(MPa/m^3)] - Ultra low		

Table 2: Dataset (ACN) for the BRNN showing data values for only the first 10 samples.

				Flexible pavement sub-grades				**Rigid pavement sub-grades**			
				CBR%				**k (MPa/m^3)**			
		Weight Max.	**Tyre Pressure**	**High**	**Medium**	**Low**	**Ultra low**	**High**	**Medium**	**Low**	**Ultra low**
S/N	**Aircraft Type**	**(kN)**	**(MPa)**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
1	A300-B-B2	1353	1.16	39	44	54	69	35	43	51	58
2	A300-B4-200	1627	1.28	50	56	69	86	46	56	66	75
3	A300-B4-200 (Optional Bogie)	1627	1.16	47	52	64	82	41	49	59	68
4	A300-B4-600R	1693	1.35	54	61	74	92	51	61	71	80
5	A300-B4-600R (Optional Bogie)	1693	1.21	50	56	69	88	44	54	64	74
6	A300-C4	1627	1.24	48	55	67	85	44	53	63	72
7	A310-200, 200C	1509	1.46	45	50	61	77	43	51	59	67
8	A310-300 (Configuration 1)	1480	1.19	44	49	61	77	40	48	57	65
9	A310-300 (Configuration 2)	1549	1.48	48	54	65	82	46	55	64	72
10	A310-300 (Configuration 3)	1617	1.29	50	57	69	86	47	56	66	75

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The BRNN Modelling and Simulation

The flow chart in figure 1 shows the algorithm that was used for training of the BRNN model. The Neural Network Fitting Tool of MATLAB (R2021a) was used to load the dataset comprising the Aircraft Classification Numbers (ACNs). A total number of 276 data values (ACNs) were presented as input to the network with 70% of the input data used for training and the remaining 30% for testing since validation is not necessary in BRNN.

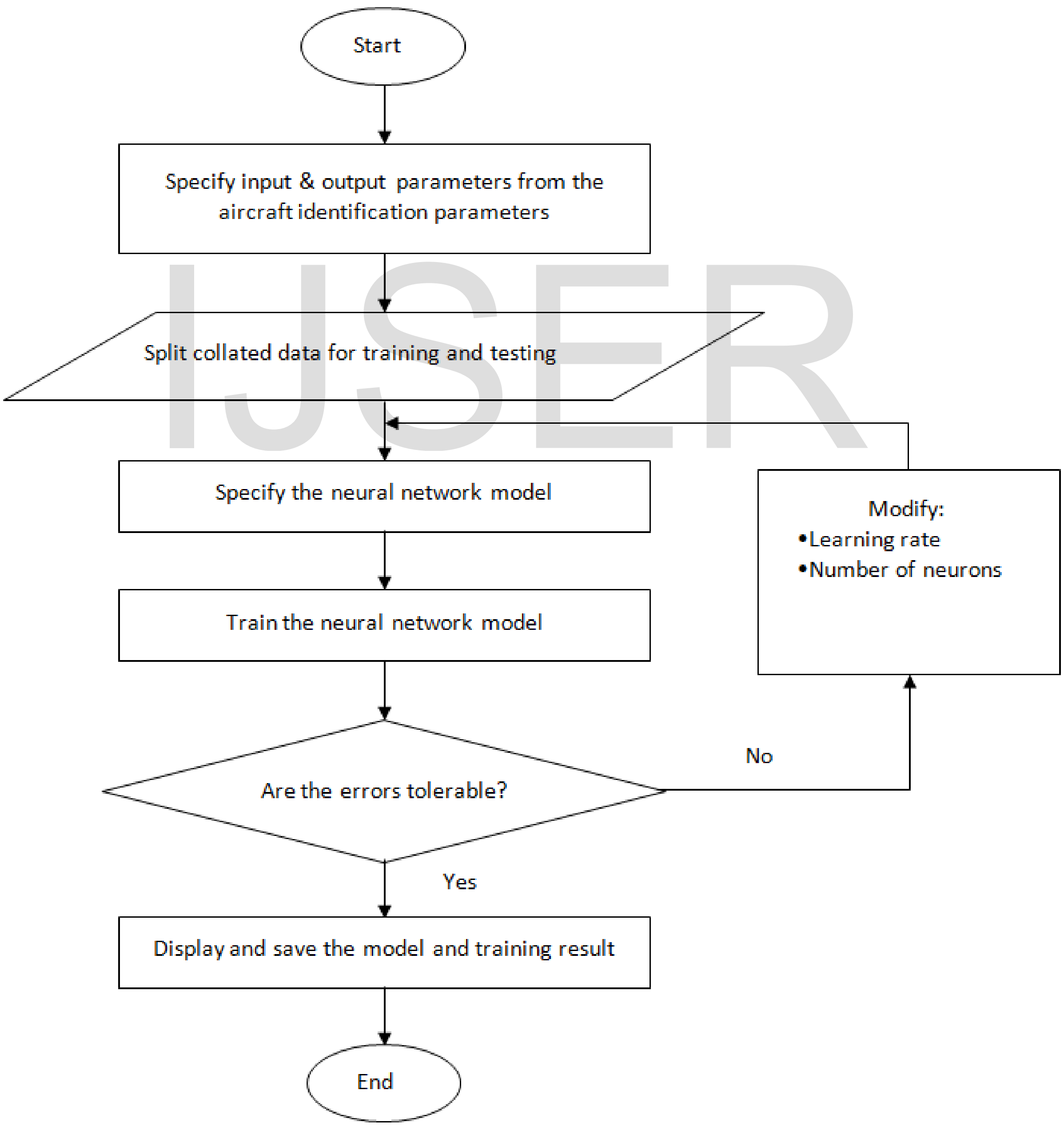

Figure 1: The BRNN model training algorithm flow chart

The standard network that was used for function fitting is a two-layer feed-forward network with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The fitting neural network is defined by the number of neurons in the hidden layer. The number of neurons in the hidden layer was adjusted after each training until the network performed well. The best result was obtained for a neural network model consisting of five neurons in the hidden layer and one neuron in the output layer as shown in figure 2.

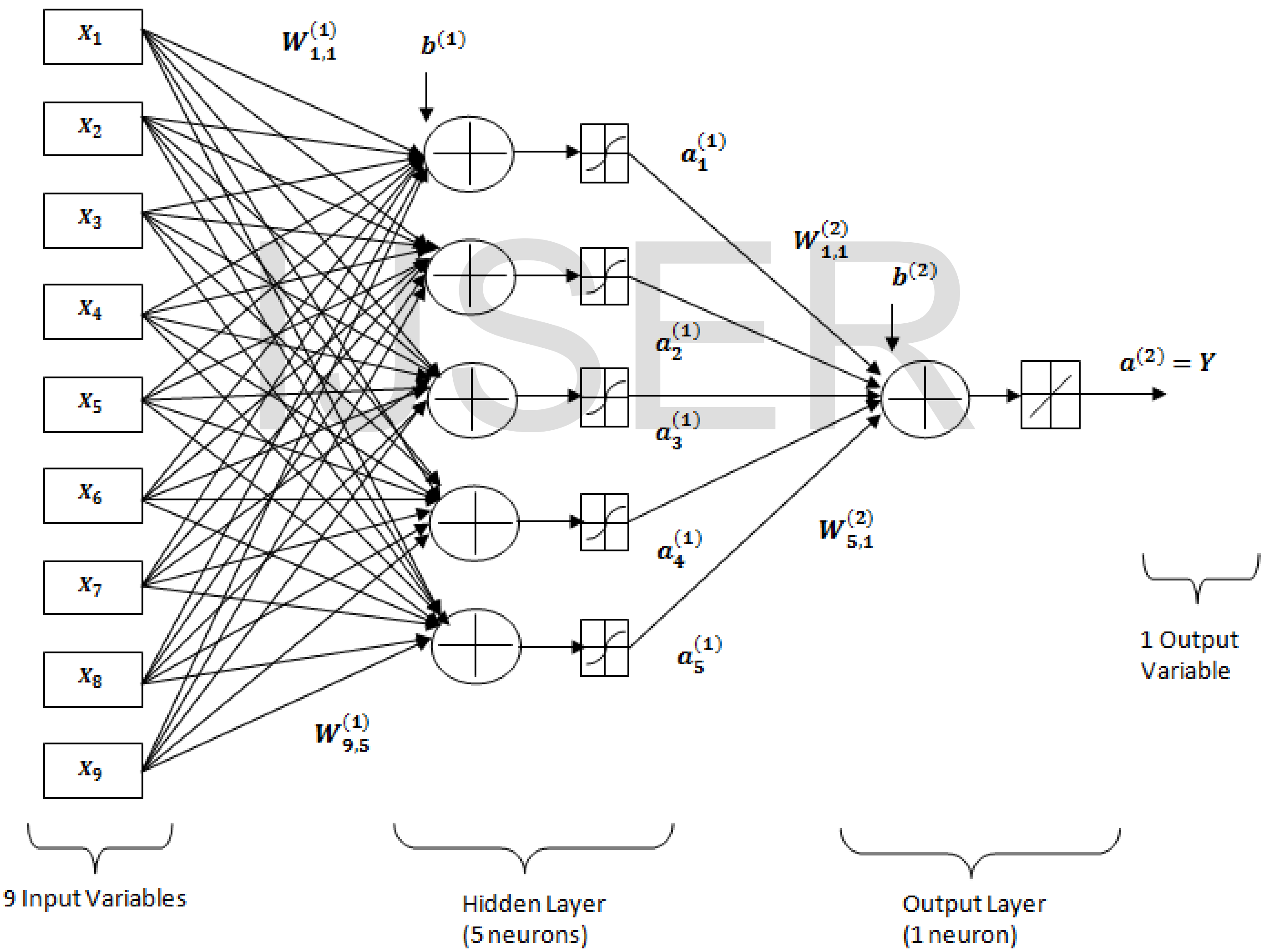

Figure 2: The architecture of the neural network model

The network training was carried out using Bayesian Regularization (trainbr) which is a network training function that updates the weight and bias values according to Levenberg-

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Marquardt optimization and minimizes errors associated with backpropagation algorithms and the likelihood of over fitting the training data. The ‘**tansig**’ and ‘**purelin**’ transfer functions were used for the hidden layer and output layer respectively. The inputs presented to the network were propagated in a forward direction and the output vector calculated through the use of a linear activation function. With each presentation, the neural network output is compared with the target (desired output); the error between them was computed and back-propagated through the network to update the connection strengths. This process of feed forward calculations and back-propagation of the error was repeated until the level of convergence between the neural network output and the target was reached.

RESULTS AND ANALYSIS

Figure 3 shows the neural network training performance indicator after the training of the neural network model.

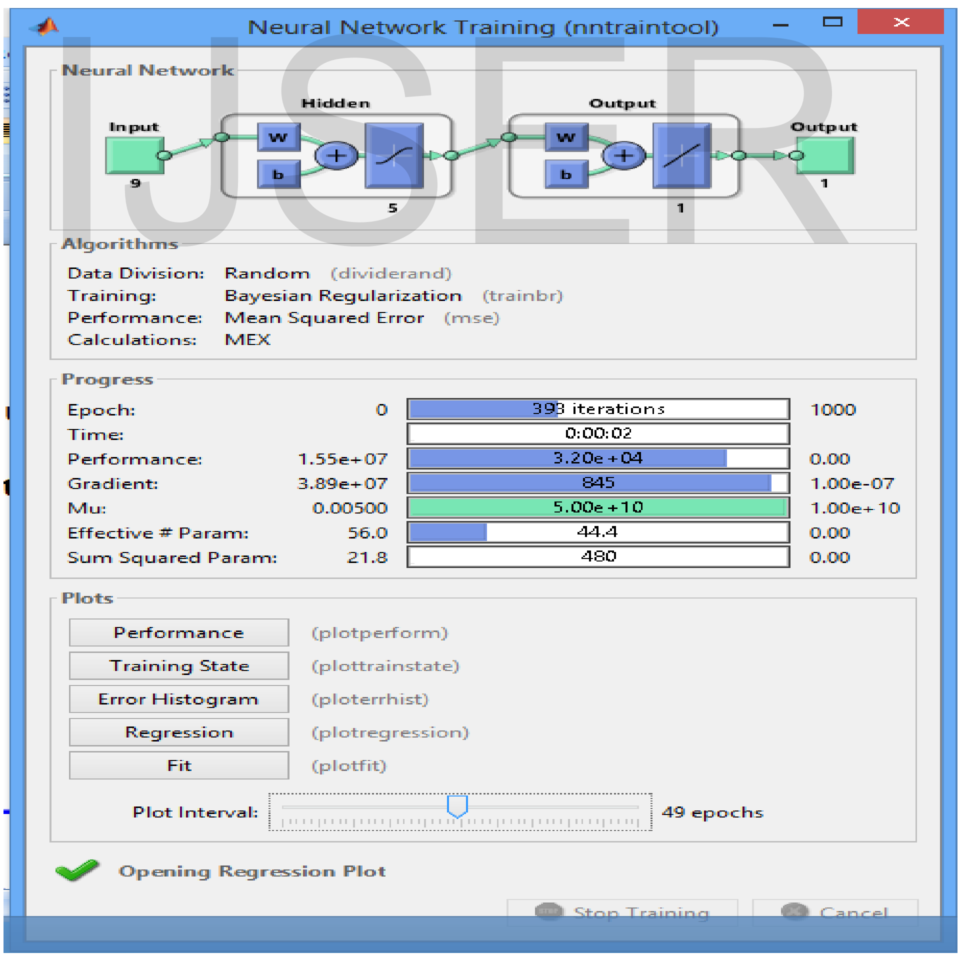

Figure 3: The neural network training performance indicator

A total of 393 iterations were executed in the training and total training time = 2 seconds as show in the neural network training performance indicator in figure 3. The plot of the neural network training state values in figure 4 shows that on reaching maximum Mu at epoch 393, the effective number of parameters = 44.4134, sum squared parameters = 480.2057 and validation checks = 0.

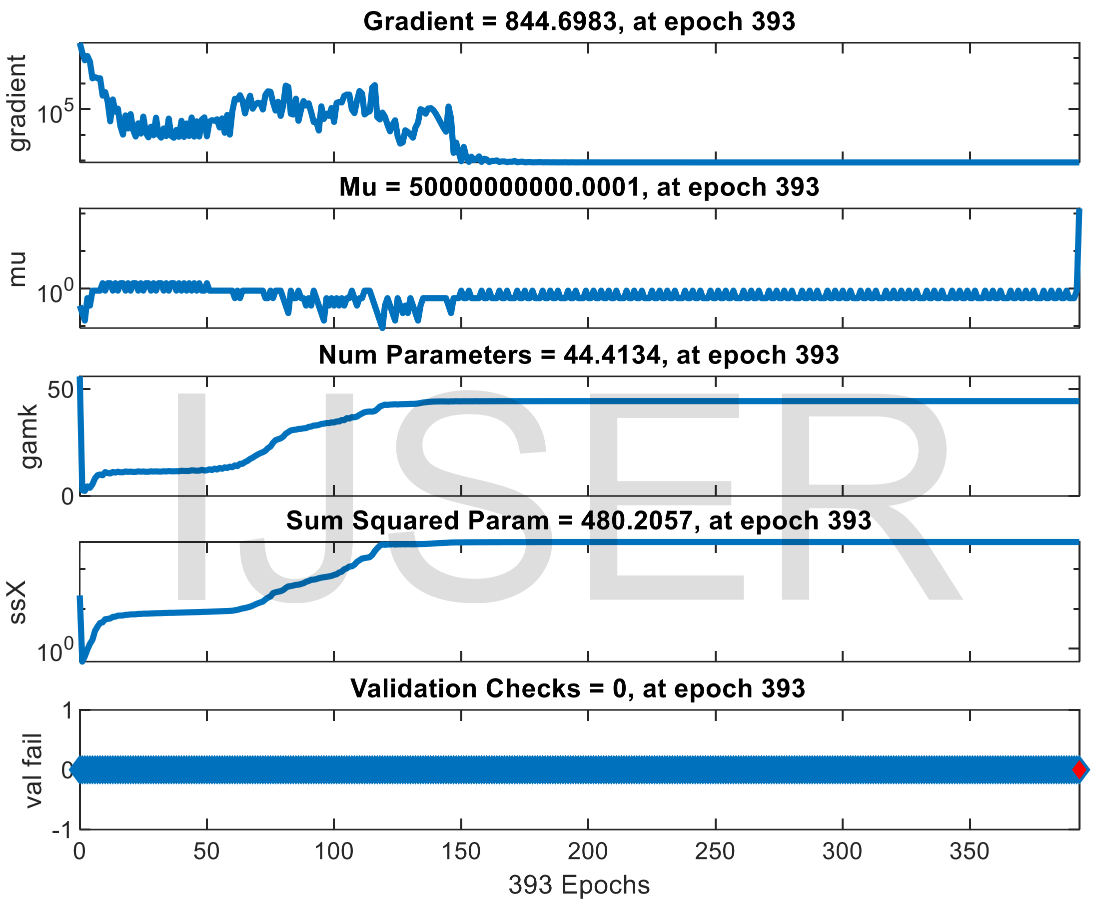

Figure 4: Plot of the neural network training state values

Plot of the linear regression of the targets relative to the outputs is shown in figure 5. The combined regression value R = 0.99015 shows that the degree of association or relatedness of the outputs and inputs is 99.015%.

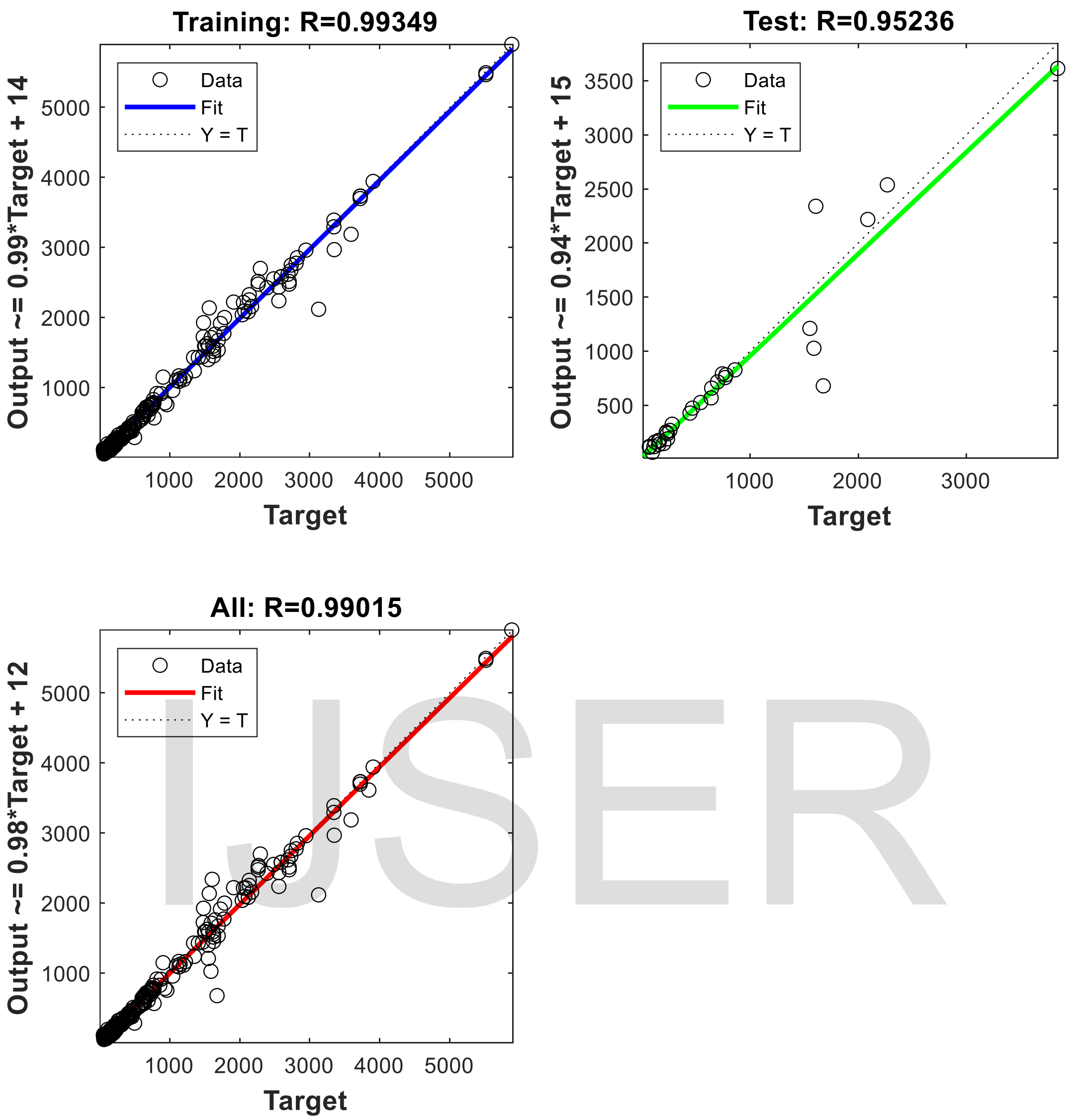

Figure 5: Plot of the linear regression of the targets relative to the outputs

Table 3 presents the neural network output for the first 10 data samples as compared with the targeted output which is weight maximum (kN) values of the aircrafts as specified in the dataset in table 2. The error values gotten were used for evaluation of the network performance

Table 3: The BRNN output as compared with the targeted output

S/N	Target Output	Network Output	Error = (Target Output - Network Output)
1	1,353.00	1,352.90	0.1
2	1,627.00	1,626.95	0.05
3	1,627.00	1,626.95	0.05
4	1,693.00	1,692.89	0.11
5	1,693.00	1,693.07	-0.07
6	1,627.00	1,626.08	0.02
7	1,509.00	1,508.97	0.03
8	1,480.00	1,479.90	0.1
9	1,549.00	1,549.40	-0.4
10	1,617.00	1,616.87	0.13

The performance and accuracy of the BRNN model was evaluated using the metrics in Table 4.

Table 4: Evaluation Metrics

METRIC	**EQUATION**	**EQUATION NUMBER**
Mean Absolute Error	$MAE = \frac{1}{m}\sum_{i=1}^{m}\lvert X_i - \hat{X}_i\rvert$	(1)
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - \hat{X}_i)^2}$	(2)
Mean Absolute Percentage Error	$MAPE = \frac{1}{m}\sum_{i=1}^{m}\lvert X_i - \hat{X}_i\rvert / X_i \times 100\%$	(3)

Where X_i is the targeted values from the historical dataset, $\hat{X}_i$ is the trained values from the neural network for *m* predicted values over a period *i*.

Table 5: Evaluation Results

EQUATION NUMBER	METRIC	RESULT
1	Mean Absolute Error (MAE)	0.097
2	Root Mean Squared Error (RMSE)	0.145017
3	Mean Absolute Percentage Error (MAPE)	1.206629%

From the evaluation results as shown in Table 5, the Mean Absolute Percentage Error (MAPE) value is 1.206629% giving an accuracy of 98.793371% calculated from the value deviation from 100%. This therefore shows that the Bayesian Regularized Neural Network (BRNN) model have a high degree of accuracy (98.79%) for aircraft identification. The implication of this is that the accuracy of the prediction can be further improved by simply adding more hidden layers and neurons but invariably slowing the convergence process.

CONCLUSION

An efficient intelligent aircraft identification system for emergency landing scheduling has been developed in this work using Bayesian Regularized Neural Network (BRNN). The Bayesian Regularization (trainbr) training algorithm proved to be efficient in producing a network that generalized well. The regression value, R = 0.99015, for the results shows that the degree to which the outputs and inputs are related and change together is 99.015%. However, the Mean Absolute Percentage Error (MAPE) evaluation of the results gave a value of 1.206629% for the network; showing a high degree of accuracy (98.79%) in the ability of the proposed Bayesian Regularized Neural Network (BRNN) solution to identify aircrafts in comparison with other solutions presented in the reviewed works and at a speed of 2 seconds.

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