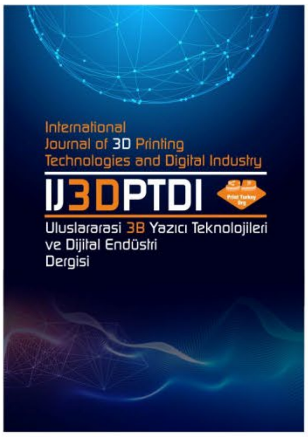

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Yazarlar (Authors): Cüneyd Demir, Cengiz Eldem, Mustafa Bozdemir

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UNMANNED GROUND VEHICLE SELECTION WITH ARTIFICIAL NEURAL NETWORKS

Cüneyd Demir[a]*, Cengiz Eldem[b], Mustafa Bozdemir[c]

[a*]Kırşehir Ahi Evran University, Mucur Vocational School, Computer Technologies Department, TÜRKİYE
[b]Gazi University, Technology Faculty, Industrial Design Engineering Department, TÜRKİYE
[c]Kırıkkale University, Kırıkkale Vocational School, Machinery and Metal Technologies Department, TÜRKİYE

* *Corresponding Author:* cuneyd.demir@ahievran.edu.tr

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ABSTRACT

In recent years, significant advancements have been made in defense systems in response to the increasing demands of countries. The importance of unmanned ground vehicles, a highly critical technology, is becoming more evident with each passing year.

In this study, a selection program is intended to be developed to determine the mission purposes for which military unmanned ground vehicles will be used. In line with the operating principles, the basic mechanical systems have been identified. Subsequently, a design catalog containing these basic mechanical systems was created. The desired features for use in the field were asked to the customer. Based on the received responses, the best alternative unmanned ground vehicles were identified using an artificial neural network algorithm.

In the artificial neural network model, a feedforward neural network architecture was used. Stochastic Gradient Descent was utilized in the network training function to minimize the model's loss function. The activation functions tanh and softmax were used, and the model has four hidden layers. The model was trained for 150 epochs. Results were obtained for the metrics of accuracy, precision, recall, and F1-score. The model's accuracy rate was found to be %99,63. Such a high accuracy rate indicates that the model has well understood the data in the dataset and provides accurate predictions.

Keywords: Defense Technology, Unmanned Ground Vehicle, Artificial Neural Networks

1. INTRODUCTION

Thanks to their nonlinear structures, artificial neural networks have been used in a wide range of fields, from engineering to data analysis. Additionally, they have found applications in various sectors such as defense, economy, industry, sports, gaming, energy, environment, and finance. Today, numerous studies have been conducted on applications of artificial neural networks.

Urgan and Tamgöz (2020) used artificial neural networks to predict the active user numbers of games on the Steam platform [1]. Özkurt (2020) demonstrated that digital transformation and artificial intelligence applications can be used to model the future position and production methods of the defense and manufacturing industries by training with artificial neural networks [2].

Ayyıldız and Demirci (2022) examined the relationship between the budget allocated for R&D activities from the central government budget and economic growth in Turkey between 2008 and 2035 using artificial neural networks [3]. Aka and colleagues (2020) predicted the end-of-season team rankings, goals scored, and goals conceded in the Turkish Super League using artificial neural networks based on input variables [4].

Köse (2021) made exchange rate predictions using artificial neural networks and grey prediction models based on exchange rate data obtained from the Central Bank of the Republic of Turkey [5]. Burçin (2023) predicted the size of vehicle loans using artificial neural networks based on monthly data from Turkey between 2006 and 2022 [6]. Şahin (2023) predicted the natural gas consumption of a house in Isparta using an artificial neural network model [7].

Ertem (2022) accurately predicted which warehouse section stored spare parts belong to by using data mining and artificial neural networks to optimize the warehouse zone assignment process [8].

Tütüncü (2022) predicted the evaporation amount using artificial neural networks based on the daily meteorological data from a station at the Atatürk Dam [9]. Karakul (2020) modeled the relationships between the Borsa Istanbul (BIST) 100 Index, overnight interest rates, and the dollar exchange rate using artificial neural networks and accurately predicted the BIST 100 Index value [10].

Buyrul (2022) modeled the mechanical properties of TiB2-added aramid fiber-reinforced composites with different orientations using artificial neural networks and statistical analyses, successfully identifying the composites with the best ballistic performance [11]. Kaya (2022) modeled the water quality parameters of Lake Iznik using artificial neural networks and accurately predicted the values of total nitrogen, total phosphorus, and dissolved oxygen [12].

Baylan and Salepçioğlu (2023) predicted the impact of strategic management tools on organizational DNA using artificial neural networks [13]. Süleymanlı (2021) predicted the gross foreign exchange reserves of the Central Bank of the Republic of Turkey using artificial neural network techniques based on data from 2013 to 2021 [14].

In recent years, studies on unmanned ground vehicles have focused on various areas such as autonomous movement, obstacle detection, route planning, agricultural applications, and various industrial uses.

Topal and Yiğit (2021) developed a low-cost and ergonomic system that enables unmanned ground vehicles to move autonomously and recognize their surroundings using a LIDAR laser scanner sensor, night vision camera, and Arduino microcontroller [15].

Kırçıl and Tepe (2024) designed a portable, low-cost, cross-platform supported, and user-friendly telemetry system that displays real-time status information and camera images of unmanned ground vehicles [16]. Sonugür (2016) developed a low-cost and highly successful auxiliary system, supported by image processing and GPS-based artificial neural networks, for unmanned ground vehicles to detect and recognize moving obstacles [17].

Kıvanç (2020) developed a specially designed outer rotor brushless DC motor that provides high torque and efficiency at low speeds, tailored for unmanned ground vehicles with omnidirectional movement capability, low friction, and high vibration. This motor is also easy to manufacture [18].

Hülako and Kapucu (2018) developed and tested a system for a microcontroller-controlled unmanned ground vehicle that reaches designated destinations using a low-cost GPS and electronic compass sensor, applying a guidance algorithm with a Kalman filter [19]. Vardin and colleagues (2022) developed a compact, remotely controlled unmanned ground vehicle prototype with four-wheel drive, operating at low speeds (<1 m/s), a carrying capacity of 5 kg, and structural strength verified by the finite element method [20].

Akdan and colleagues (2023) developed an autonomous and solar-powered agricultural unmanned ground vehicle equipped with a depth camera, convolutional neural network-based detection algorithm, and an innovative suspension system, capable of locally treating harmful plants in agricultural fields with 90% accuracy [21]. Bayram and colleagues (2022) successfully implemented path-following control based on position and orientation error feedback using an unmanned ground vehicle equipped with RTK-GPS, IMU, and absolute encoder sensors, utilizing a successively linearized and discretized kinematic model predictive control [22].

Gökçe and Sonugür (2018) compared the performance of two image processing-based auxiliary systems for detecting moving objects on the routes of unmanned ground vehicles using geographic location data and artificial neural networks [23]. Naglak and colleagues (2021) designed a low-cost, compact, and adjustable cable management mechanism to facilitate the distribution of electrical cables by unmanned ground vehicles in mobile microgrid systems, and explained how to recreate this mechanism [24].

Patel and colleagues (2022) developed an asphalt layer change classifier to automatically monitor road construction progress using sensors mounted on unmanned ground vehicles, achieving a 97.88% accuracy rate with the ConvLSTM algorithm, demonstrating the potential to increase efficiency in road construction projects [25]. Zhou and colleagues (2020) presented a strategy for global and local trajectory planning using an artificial fish swarm algorithm and a Markov chain-based trial-and-error search algorithm to ensure unmanned ground vehicles reach their targets safely in dynamic environments [26]. Mei and colleagues (2022) introduced the ROADS prototype, a multi-sensor unmanned ground vehicle for monitoring road degradation, showing that road condition assessments can be conducted with 74.2% accuracy using an image-based method [27].

Chung and colleagues (2021) provided information on an unmanned ground vehicle designed and developed to detect crevasses in Antarctica and prevent accidents. This vehicle can adapt to harsh terrain conditions and operate at a speed of 2.5 m/s for over two hours [28]. Liu and colleagues (2022) presented a path planner for multiple unmanned ground vehicles that uses continuous ant colony optimization for path planning and coordination, demonstrating superior performance in complex and high-dimensional problems [29]. Wang and colleagues (2020) designed a new modeling and path planning framework for unmanned ground vehicles with specific sensing capabilities, enabling them to continuously monitor events occurring at unknown locations and probabilities by moving through a road network with different priorities [30]. Hassan and colleagues (2023) designed a control system using the double deep Q-network (DDQN) algorithm to ensure unmanned ground vehicles follow the desired path. Simulation results demonstrate that this system operates with high accuracy even under noisy conditions [31].

With advancing technology, unmanned ground vehicles find applications in various fields such as defense, agriculture, logistics, and exploration. The correct selection and configuration of these vehicles are crucial for their effective and efficient performance. Today, advanced artificial intelligence techniques like artificial neural networks play a critical role in the processes of selecting and optimizing UGVs according to environmental conditions and mission requirements. This study examines the methods, advantages, and research gaps in the selection of UGVs using ANNs. The aim is to enhance the operational success of UGVs by determining an appropriate ANN model. The absence of a selection program specifically for military-purpose UGVs and its lack of integration with artificial intelligence make this study unique.

2. MATERIAL AND METHOD

A selection program has been developed to determine the tasks for which military unmanned ground vehicles will be used. Within this program, the fundamental mechanical systems of UGVs have been identified based on their operating principles. Subsequently, a design catalog containing these fundamental mechanical systems was prepared. The desired features of the UGV to be used in the field were gathered from customers, and based on the responses, the most suitable UGV was developed using an artificial neural networks algorithm.

2.1. Unmanned Ground Vehicle

The development of unmanned ground vehicles began in the 1970s with research examining the feasibility of legged machines. These studies revealed that before producing a walking machine, it was necessary to develop a robot equipped with specific equipment to perform the targeted tasks. Over time, this research was particularly adapted for military applications, leading to concrete steps in the development of UGVs [32].

Unmanned ground vehicles are among the autonomous systems expected to play a significant role in the future armies. These vehicles are designed to minimize battlefield risks and neutralize threats using their electronic vision systems, various sensors, and remotely controlled weapon systems. These sensors enable the vehicle to perceive its surroundings, map the terrain, and navigate effectively. Additionally, these vehicles often utilize artificial intelligence (AI) and machine learning algorithms to process environmental data and make decisions [33].

According to current definitions, UGVs are described as vehicles with high mobility and adaptable platforms that can integrate mission-specific modules. These vehicles, which can be remotely controlled with adjustable levels of autonomy and modular control consoles, are referred to as next-generation unmanned systems that advance by maintaining contact with the ground [34].

Unmanned ground vehicles are used in the military for tasks such as infiltrating enemy lines, armed attacks, bomb disposal, logistics, mine detection, and surveillance. In the civilian sector, they are effectively utilized in agriculture, firefighting, environmental monitoring, and infrastructure inspection. UGVs play a crucial role, especially in disaster management and emergency response [35].

Unmanned ground vehicles in the defense sector are distinguished by their capacity to operate in dangerous and hard-to-reach areas. These vehicles can undertake reconnaissance, surveillance, and direct combat missions during military operations without risking human lives. Equipped with advanced sensor packages and autonomous navigation systems, they can maneuver effectively even in complex battlefield environments. These features make them critical assets that enhance strategic advantages on the battlefield. As technological advancements make UGVs increasingly indispensable, they also underscore the need for ethical and legal regulations. The use of UGVs brings new debates in the realms of the laws of war and military ethics. Their operational capabilities are reshaping the role of unmanned systems in military disciplines, leading to significant changes in defense strategies [36].

Unmanned ground vehicles are being developed for armed forces worldwide and have the potential to replace traditional tanks as dominant combat vehicles. Over the past decade, UGV technology has made significant advances in the defense sector. Countries such as the United States, the United Kingdom, China, Europe, and Turkey are among those heavily investing in the development of robotic combat vehicles. The global unmanned ground vehicles market, valued at an estimated USD 2.54 billion in 2020, is expected to grow at a compound annual growth rate of 6.5% from 2022 to 2029, reaching USD 3.91 billion by 2029. This growth is driven by the strategic and operational advantages of UGVs, as well as increases in defense budgets [37].

The general design of unmanned ground vehicles involves numerous subsystems and a complex network of relationships among them that directly influence the design. Design-related requirements are evaluated based on these existing system relationships, and a data set has been created to determine the most optimal solution. This data set consists of 15 parameters included in the design catalog: autonomous structure, control system, payload, body material, motor, energy system, power transmission system, braking system, thermal management system, electrical system, guidance system, suspension system, mobility configuration, chassis, and electronic units (Table 1).

Artificial neural networks with decision-making structures require some responses from the designer or customer to generate suitable alternatives. The questions to be used in inference development for the decision-making structure are listed below.

1. What should be the cost of the unmanned ground vehicle? *(Low, Medium, High)*
2. What should be the dimensional classification of the unmanned ground vehicle? *(Light, Small, Medium, Heavy)*
3. What should be the autonomy level of the unmanned ground vehicle? *(Level 1, Level 2, Level 3)*
4. What should be the coverage area of the unmanned ground vehicle? *(x<2 km², x<5 km², x km²)*
5. What tasks is the unmanned ground vehicle expected to perform? *(Reconnaissance, surveillance and intelligence, bomb disposal, attack and rear security, logistics, mine and obstacle clearance)*
6. What type of motor should be used in the unmanned ground vehicle?
   (0-20 kW, 20-75 kW, 75-300 kW, 300+ kW,
   25-100 Hp, 100-400 Hp, 400+ Hp,
   25-100 Hp + 0-20 kW,

100-400 Hp + 20-75 kW,
400+ Hp + 75+ kW)

7. On what types of terrain will the unmanned ground vehicle be used? *(Flat hard ground, flat soft ground, rough hard ground, and rough soft ground)*
8. What level of maneuverability should the unmanned ground vehicle have? *(Large turning radius, medium turning radius, and small turning radius)*

The alternatives in the solution space created with the design catalog parameters have been evaluated using the questions mentioned above. Out of 907.200.000 alternatives, the ones that will ensure the system's functionality have been identified (Figure 1).

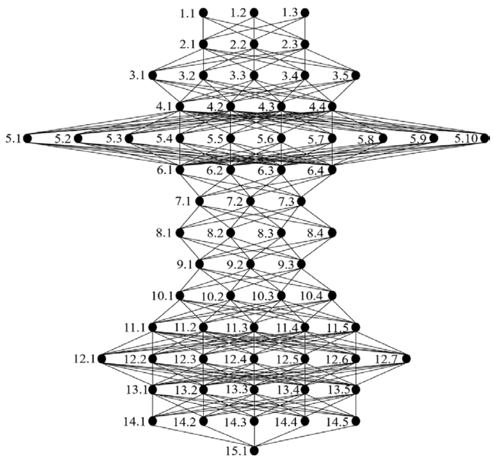

Figure 1. Solution space

2.2. Artificial Neural Network

Artificial neural networks (ANNs) are systems designed to mimic the working principles of neurons in the human brain. These systems consist of simple processors interconnected at varying levels of influence, forming a decision-making mechanism based on learning capability. Early studies focused on the mathematical modeling of biological cells (neurons) in the brain. These studies demonstrated that each neuron transforms information received from neighboring neurons into an output in a manner consistent with the dynamics of biological neurons [38].

Figure 2 illustrates a neuron model as a basic element. Data from the external environment are connected to the neuron via weights, which determine the influence of the input. The result obtained from the multiplication of inputs and their respective weights forms the net input. This process is carried out through the summation function. The activation function computes the net output during the processing phase, which also constitutes the neuron's output. The activation function is usually a nonlinear function. The constant “b” represents the bias or the threshold value of the activation function. The “w” represents the weights, “x” represents the inputs, and “f” represents the activation function. Variables x_1, x_2, x_3, ..., x_m represent the n number of inputs to the neuron, and variables w_1, w_2, w_3, ..., wm represent the weights associated with these inputs. A basic artificial neural network cell is much simpler than a real neuron, consisting primarily of components like the input vector (x) and the weight vector (w). In the multilayer perceptron and backpropagation model, (w) is used as a matrix instead of a vector [39].

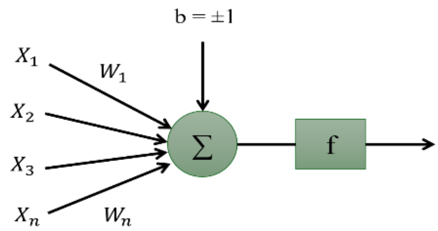

Figure 2. Artificial neural network cell [40]

The initial element compares the total value obtained by summing the products of the inputs and their respective weights with a given initial value. When this total is compared to the initial value, if the total is higher, the output value is calculated using a nonlinear function (F). The output signal y is the result of the nonlinear function (F) of the difference between the total and the initial value. Here, x_i is the input signal, w_i is the weight associated with x_i, and (F) is the nonlinear function, as expressed in Equation 1. The nonlinear function F is determined based on the modeling choice and the desired output type of the artificial neural network model.

$$y = F\left(\sum w_i x_i + b\right) \quad (1)$$

An artificial neural network consists of three layers: input, hidden, and output layers (Figure 2). The first layer, the input layer, allows data to enter the neural network. Data from this layer is processed and sent to the output layer. The hidden layer, which performs the main function of the network, transmits signals from the input layer to the output layer. The number of hidden layers can vary in different networks depending

on the application's purpose [41]. The final layer, the output layer, processes data from the hidden layer and produces results based on the data received from the input layer.
Additionally, an artificial neural network consists of three fundamental components: the architecture, the learning algorithm, and the activation function [42]. The architecture includes the layers, neurons, and the connections between neurons. The learning algorithm calculates probabilities based on input data and determines the likely outcomes. The activation function processes the input data to generate the results.

A neuron is located in a network with numerous feedback connections. Many networks consist of simple processor elements, and their basic structures are typically single-layered. Applications in various fields have demonstrated the limited capabilities of single-layer networks. However, these types of networks later led to the development of multilayer networks, which are formed by integrating two or more neural layers. In the multilayer networks shown in Figure 3, the number of neurons in each layer can vary, and the output of each layer is created as a weighted sum of the outputs from the previous layer. Researchers have developed algorithms for the systematic training of multilayer networks. The application of these algorithms to multilayer networks has yielded superior results compared to single-layer networks [43].

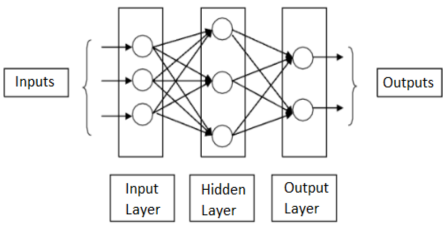

Figure 3. Multilayer neural network [40]

Activation functions used in artificial neural networks are mathematical functions employed to process input signals to produce outputs for the neural networks. These functions determine the output of each neuron in every layer of the neural network. The functions of activation functions significantly influence the learning rate and the training process of the model. Table 2 provides the most common activation functions and their mathematical formulas.

<u>Hyperbolic Tangent Function (Tanh):</u> The Tanh function transforms the input into a value between -1 and 1, providing more symmetric output. Since the gradient of the Tanh function is larger, the vanishing gradient problem is less pronounced during training [44]. However, the vanishing gradient problem can still occur in deep neural networks, especially with very large values.

<u>Softmax Function:</u> Normalizes the elements of a vector to be between 0 and 1. It is used in multi-class classification problems and its outputs can be interpreted as a probability distribution. The Softmax function is specifically tailored for classification problems.

Table 2. Activation functions

Activation Function	Formulas	
Sigmoid	$\sigma(x) = {}^{1}/_{(1+e^{-x})}$	0,1
Relu	$f(x) = \max(0, x)$	0, ∞
Tanh	$\tanh(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})}$	-1,1
Softmax	$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}}$	0,1

3. EXPERIMENTAL FINDINGS

The created model features a feedforward backpropagation neural network architecture. To minimize the model's loss function, the SGD (Stochastic Gradient Descent) algorithm, one of the most commonly used optimization algorithms in neural networks and machine learning models, has been utilized in the network training function. The activation functions used are Tanh and Softmax. The model comprises four hidden layers with 64, 128, 64, and 16 neurons, respectively. The model was trained for 150 epochs, with 60% of the dataset used for training, 20% for testing, and 20% for validation. Table 3 and Figure 4 provide information and visual representations related to the model.

Table 3. Model of network architecture

Network Type	Feed Forward Backprop
Training Function	Stochastic Gradient Descent
Activation Function	Tanh-Softmax
Hidden Layer	4 (64, 128, 64, 16)
Epoch	150
Training Data	%60
Test Data	%20
Validation Data	%20

Table 1. Unmanned ground vehicles design catalog

		DESIGN CATALOG									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**Autonomous Structure**	Manuel	Semi-Autonomous	Autonomous							
2	**Control System**	RF Control	Remote Control Module	Satellite							
3	**Payload**	Surveillance System	Manipulator System	Carrier System	Weapon System	Mine and Obstacle Clearing System					
4	**Body Material**	Polymer Materials	Composite Materials	Aluminum Alloys	Steel Alloys						
5	**Engine**	0-20 kw	20-75 kw	75-300 kw	300+ kw	25-100 Hp	100-400 Hp	400+ Hp	25-100 Hp + 0-20 kw	100-400 Hp + 20-75 kw	400+ Hp + 75+ kw
6	**Energy System**	Cell Battery	Battery	Fuel Cell	Fuel Tank						
7	**Powertrain System**	Fixed Ratio Transmission	Electric Transmission	Variable Ratio Transmission							
8	**Brake System**	Dynamic Braking	EBS	ABS	Regenerative Braking						
9	**Thermal Management System**	Air Cooled	Oil Cooled	Water Cooled							
10	**Electrical System**	Accumulator Free	12V Accumulator	24V Accumulator	28V Accumulator						
11	**Steering System**	Ackerman	Differential	4WS	Skid-Steer	Independent Steering					
12	**Suspension System**	Rubber-Elastomeric	Spring and Shock Absorber Systems	MacPherson Strut	Double Wishbone	Torsion Beam	Solid Axle	Hydropneumatic			
13	**Mobility Configuration**	2-Wheeled	4-Wheeled	6-Wheeled	8-Wheeled	Tracked					
14	**Chassis**	2-Wheeled Chassis	4-Wheeled Chassis	6-Wheeled Chassis	8-Wheeled Chassis	Tracked Chassis					
15	**Electronic Units**	Sensors-Cameras-Processors-Power Distribution Units-Cables									

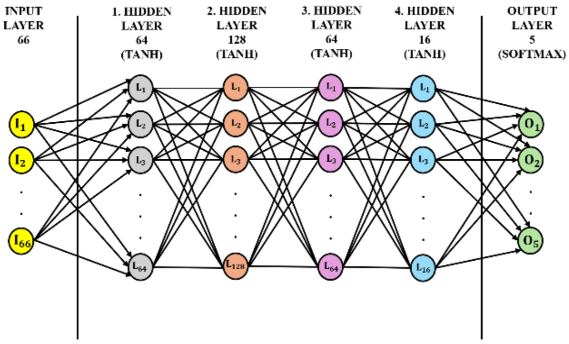

Figure 4. ANN model

The table shows the performance metrics of the model for different classes. The overall model accuracy is %99.6, indicating a very high performance across all classes. The model achieved flawless classification across the 2-wheel, 6-wheel, and 8-wheel categories, demonstrating %100 performance in all metrics. In the 4-wheel category, the model achieved %100 precision; however, the recall rate was slightly lower at %98, resulting in an F1 score of %99. In the tracked vehicle category, the model exhibited near-perfect performance with %99 precision, %100 recall, and a %100 F1 score. Overall, the model is observed to be highly reliable and high performing across all vehicle categories.

Table 4. Model performance metrics

Class	Accuracy	Precision	Recall	F1 Score
2 Wheeled	0.996	1.00	1.00	1.00
4 Wheeled		1.00	0.98	0.99
6 Wheeled		1.00	1.00	1.00
8 Wheeled		1.00	1.00	1.00
Tracked		0.99	1.00	1.00

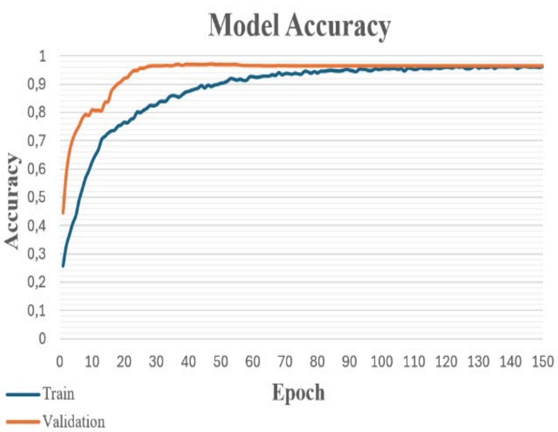

Figure 5. Model accuracy graph

The model quickly achieves a high level of accuracy on the validation data and maintains this accuracy. The loss on the training data steadily decreases and continues to decline throughout the learning process. This indicates that the model is successful in its learning process and optimizes its performance on both validation and training data (Figure 5).

The model consistently reduces the loss during training, indicating that the learning process is effective. The validation loss decreases rapidly during the initial epochs and then stabilizes at a certain value. This demonstrates that the model performs steadily on the validation data. The overall view of the loss values in Figure 6 shows that the model progresses well during training, the learning process occurs in an orderly manner, and signs of overfitting are not very pronounced.

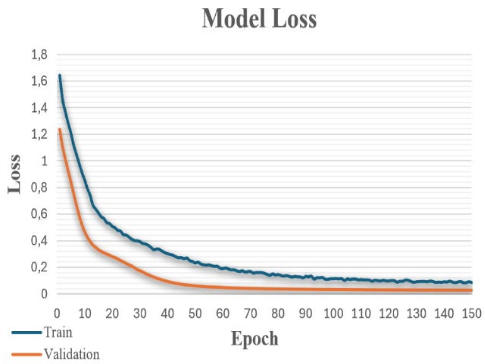

Figure 6. Model loss graph

The classification performance of the model is displayed on a confusion matrix graph. Out of thousands of designs, it does not appear to be an external error factor in mistakenly learning 12 tracked vehicles as 4-wheeled vehicles (Figure 7).

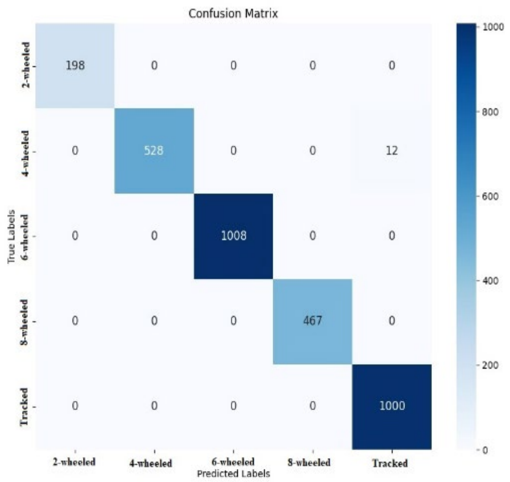

Figure 7. Confusion matrix graph

4. RESULTS

Artificial neural networks have been applied to various fields such as defense, economy, industry, sports, gaming, energy, environment, and finance. Unmanned ground vehicles, on the other hand, have been used in autonomous movement, obstacle detection, route planning, agricultural, and various industrial applications. In light of all this information, it has been observed that no study has been conducted on the selection of unmanned ground vehicles using artificial neural networks.

Artificial neural networks have been applied in various fields such as defense, economy, industry, sports, gaming, energy, environment, and finance. Unmanned ground vehicles, on the other hand, have been used in autonomous movement, obstacle detection, route planning, agricultural, and various industrial applications. In light of all this information, it is evident that no study has been conducted on the selection of unmanned ground vehicles using artificial neural networks.

In this study, an innovative selection program has been developed using artificial neural networks to determine the optimal choice for unmanned ground vehicles. By processing multidimensional data and leveraging their learning capabilities, artificial neural networks can make highly accurate decisions in selecting unmanned ground vehicles. Based on feedback received within the framework of eight specified questions, the design catalog and the system have quickly and effectively identified the best alternatives.

These results expand the potential application areas of neural network-based decision support systems in the defense industry and other critical sectors. The unmanned ground vehicle selection process demonstrates that similar methods can be applied to other unmanned systems as well. The flexible and adaptable structure of the developed model proves that it can quickly adjust to different future conditions and requirements.

This study has revealed that all parameters in unmanned ground vehicles are interrelated. It has been determined that creating a mobility system capable of operating in all types of terrain conditions is quite challenging. In a traditional design process, it is known that the design of an unmanned ground vehicle begins with the selection of the mobility system. Thanks to the answered questions and the data set used, the most suitable mobility system has been identified using artificial neural networks.

With this method, the time required for the designer to evaluate alternatives according to all criteria has been shortened, and the design costs have been reduced. In the event of the commercialization of the unmanned ground vehicle selection program, it has been clearly demonstrated that various unmanned ground vehicle designs can be realized according to customer demands.

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