Smart Road Surface Condition Analysis via WOA-BP Neural Network and Multi-Sensor Integration

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***Abstract*—The proper identification of road surfaces is essential for enhancing traffic safety. But current approaches can't handle varying road surfaces, and detection accuracy should be better. In order to improve detection accuracy, this research introduces a novel road surface condition monitoring system called WOA-BP. The system leverages multi-sensor data. Testing was carried out in a temperature range of -30℃ to 50℃ to confirm the efficacy of the model. The WOA-BP neural network model achieved better detection accuracy and model stability compared to BPNN, SVM, and RF. It has a 98.8 percent success rate in identifying snowy, ice, dry, and rainy environments. By modifying the BPNN's starting weights and thresholds with the WOA, we can improve classification performance and resilience by decreasing the number of local optima and the rate of convergence. Collaboratively, the microwave water film thickness sensor, capacitive road condition sensor, and temperature sensor enhance detection accuracy. This research delves into the topic of intelligent transportation systems and traffic safety by investigating how to accurately identify road conditions using the WOA-BP neural network.**

***Index Terms*—Ice formation detection, Pavement condition assessment, WOA-optimized BP neural network, Sensor data fusion, Whale Optimization Algorithm**

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I. INTRODUCTION

THE major challenge to maintaining safe driving conditions is the negative impact of precipitation on roads, including snow and rain [1]. Vehicles are more likely to skid and lose control when there is water, ice, or snow on the road because these elements reduce tire-road friction [2]. According to research, the frequency of traffic accidents increases between fifty percent and one hundred percent when roads are wet compared to dry roads. Moreover, the frequency of accidents on snowy roads is significantly higher than that on wet roads [9]. According to research by Eisenberg et al. [3], which looked at over 30 million road incidents in the US, more people died and more property was damaged on snowy days than on dry ones. An increase in accident rates can be attributed, in large part, to drivers' tendency to misjudge conditions, such as thin ice or surfaces coated in snow [4]. Driving is already dangerous enough without having to contend with reduced visibility, which makes it even more difficult for drivers to spot potentially dangerous road conditions. In addition to helping management departments come up with suitable traffic management strategies, providing drivers with up-to-date and accurate information about road conditions allows them to effectively change their routes and speeds [5]. Consequently, it is critical to improve traffic safety by developing technology that accurately detects the condition of road surfaces.

Enhancing the accuracy and reliability of road condition detection primarily focuses on two key areas: the development of advanced sensors utilizing innovative materials and technologies, and the exploration of novel algorithms. Road surface condition sensors are generally classified into contact and non-contact types, based on their underlying measurement principles [6]. Non-contact sensors operate using technologies such as radar, infrared, and visible light. Systems that rely on the visible spectrum typically employ vehicle-mounted or roadside cameras to capture images, which are then analyzed through specific algorithms to assess the condition of the roadway. In recent years, there has been a notable increase in the application of algorithms for non-contact road surface monitoring. These include vision transformers [9], ResNet50, Mask-RCNN [8], and partial least squares (PLS) k closest neighbor (KNN) [10]. As an example, Jonsson et al. [10] used PLS to assess weather data and image data, effectively classifying conditions as dry, wet, icy, or snowy. The accuracy of nighttime road condition assessment was improved by 89% for wet surfaces and 96% for snow-covered areas when Kawai et al. used KNN to evaluate photos taken by cameras mounted on vehicles [11]. Despite their usefulness in determining basic road surface characteristics, non-contact detection systems confront a number of obstacles. Because of their high price tag and poor performance in poor lighting or adverse weather (such as dense fog or heavy snowfall), these sensors have limited use [12]. A further concern is that these methods cannot detect black ice that is hidden under snow, which increases the likelihood of traffic accidents [13].

Contact sensors, on the other hand, are less susceptible to outside interference, allowing them to provide more reliable detection findings when exposed to materials such as water, ice, or snow. Several principles, including capacitance [14], resonant piezoelectric [15], fiber optics ultrasonic [16], and conductance [17], underpin the operation of contact sensors. Troiano et al. developed a capacitive sensor that can differentiate between air, water, and ice using multi-frequency excitation, which is both efficient and cost-effective [17]. A touch sensor made of concrete that can detect changes in resistance and temperature effectively distinguishes between dry, wet, and black ice was developed by Tabatabai and colleagues [18]. Improving the precision of detecting road surface conditions requires not only the optimization of sensors but also the use of sophisticated algorithms. As an example, a team led by Chen et al. achieved an impressive 89% accuracy in distinguishing water, ice, and ice-water combinations using a fork-finger planar capacitive sensor that was combined with a decision-making system [19]. Additionally, a thin-film impedance sensor was developed by Gui et al. by integrating machine learning techniques with information pertaining to impedance spectrum correlation. With a 93.1% accuracy rate in classifying five different states, including dry, water, and ice-water combinations, the SVM models showed remarkable performance [20]. But these systems can't handle the impact of temperature and film thickness on detection accuracy because they only use one sensor [21]. Also, there are a lot of problems with the current methods when it comes to snow detection. On the other hand, by combining data from multiple sensors, interference issues can be greatly reduced, leading to more accurate detection of road surface conditions.

The complimentary nature of inter-sensor data has allowed for the integration of multi-sensor information to play an increasingly important role in recent years, enhancing the reliability of sensor outputs across a variety of domains [22], [23]. One common approach to fusing data from several sensors is the BP neural network (BPNN), which is well-known for its excellent nonlinear mapping capabilities [24]. But because BPNN's initial weights and thresholds are chosen at random, the training process could converge to a local minimum, affecting the accuracy of predictions [25]. Hence, it has been combined with smart optimization algorithms like PSO, genetic algorithm, and whale optimization algorithm (WOA) [26] to help it break out of its local minimum. Of them, WOA stands out due to its impressive global search capabilities and local extremum evasion strategies, which have proven to be highly effective when paired with BPNN in a range of domains. In addition, WOA's consistent performance is improved by its low demand for parameter adjustment. Despite the WOA-BP neural network's remarkable capabilities, its use in detecting road surface conditions has not been investigated yet.

This study aims to enhance detection accuracy by integrating outputs from multiple sensors and introducing a Backpropagation Neural Network (BPNN) optimized using the Whale Optimization Algorithm (WOA) for assessing road surface conditions. The system was tested under various scenarios, including dry, wet, icy, and snowy surfaces, using a contact-based road condition sensor in combination with additional sensors. The proposed method was validated within a temperature range of -30°C to 50°C. It achieved a high average accuracy of 98.8% across multiple experiments, demonstrating superior performance and stability compared to traditional BPNN, Support Vector Machine (SVM), and Random Forest (RF) models. Specifically, the classification accuracy for dry, wet, slippery, and snowy conditions reached 98.2%.

II. DETECTION OF ROAD SURFACE CONDITIONS UTILIZING THE WOA-BP MODEL

A. Enhancement of the BP neural network

A Backpropagation Neural Network (BPNN), a subtype of artificial neural networks (ANNs), consists of an input layer, one or more hidden layers, and an output layer. It employs the backpropagation algorithm to compute the gradient of the loss function with respect to each weight and bias. Through iterative updates using gradient descent or its modified versions, the network reduces the error between predicted and actual outputs until it meets a predefined accuracy threshold [27]. In this study, a three-layer BPNN model was developed to classify road surface conditions. The model utilized input features such as temperature, voltage variation, and water film thickness to predict four surface states: dry, wet, icy, and snowy.

Backpropagation neural networks (BPNNs) typically start with random values for their weights and thresholds and refine them through backpropagation until the network's error is reduced. However, the network easily converges to local minima because to the arbitrarily set initial weights and thresholds; training results vary greatly depending on the starting parameters. These issues have the potential to greatly affect the BPNN's prediction accuracy and convergence speed. An efficient swarm intelligence technique that draws inspiration from hump-back whale foraging behavior, the whale optimization algorithm (WOA) is renowned for its strong global search capabilities to find best solutions [28]. This research makes use of the WOA to supplement the BPNN, which improves its ability to generalize and make predictions. By modifying the initial weights and thresholds for BPNN using WOA, the problem of the network getting stuck in local minima is effectively eliminated.

A detailed algorithmic approach for optimizing the BPNN using WOA is shown in Figure 3. We also detail the whole processes for improving BPNN's initial weights and thresholds using WOA.

B. Development of the WOA-BP neural network model

In this research, a WOA-BP neural network model was developed using MATLAB, consisting of three layers: an input layer, a hidden layer, and an output layer. The detailed structure of the WOA-BP neural network is illustrated in Figure 2. The input layer comprises three neurons corresponding to the input parameters: temperature, voltage fluctuation, and water film thickness. The output layer includes four neurons, each representing a specific road condition—dry, wet, icy, and snowy. The number of neurons in the hidden layer, denoted ash, significantly affects the model's performance and was determined experimental validation [29]. Here, m and n refer to the number of neurons in the input and output layers, respectively, and k is an integer ranging from 1 to 10. After rigorous testing, 10 neurons were selected for the hidden layer. Additionally, the activation function used for the hidden layer was MATLAB's tansig function was applied for the output layer.

III. SYSTEM DESIGN FOR DETECTING ROAD

We used a WOA-BP neural network to construct a sensor-fusion-based road condition detection system (Figure 3) that could achieve high-accuracy road condition identification. Gathering data from road condition sensors, preprocessing it, fusing features from many sources, transmitting it, and finally, using a trained WOA-BP neural network to recognize road conditions are the parts that make up this system. In this study, we integrate data from many sensors by using feature-level fusion. By allowing the merging of different types of sensor data, feature-level fusion provides more comprehensive insights.

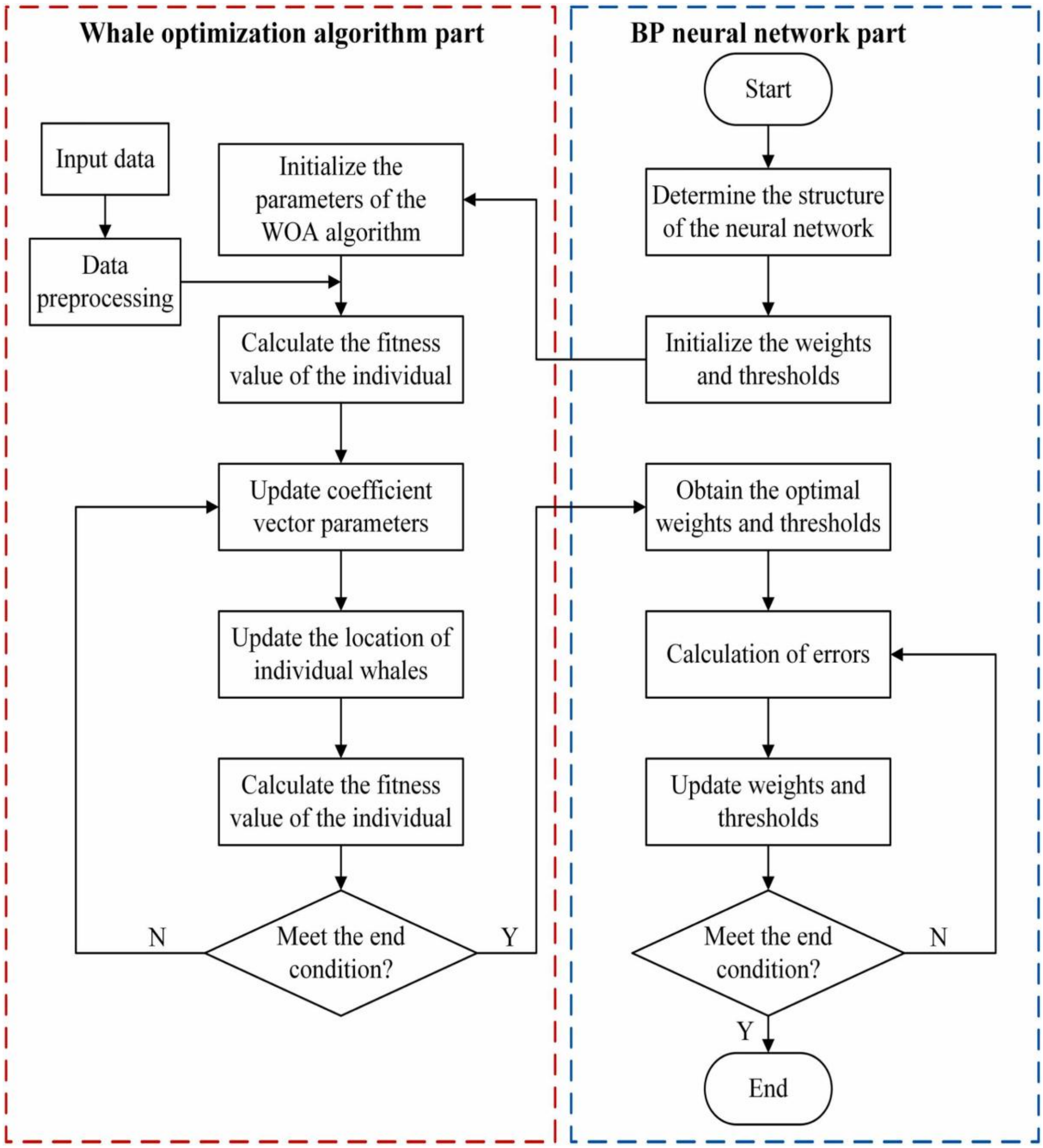

Fig. 1. The flowchart of the WOA-BP neural network

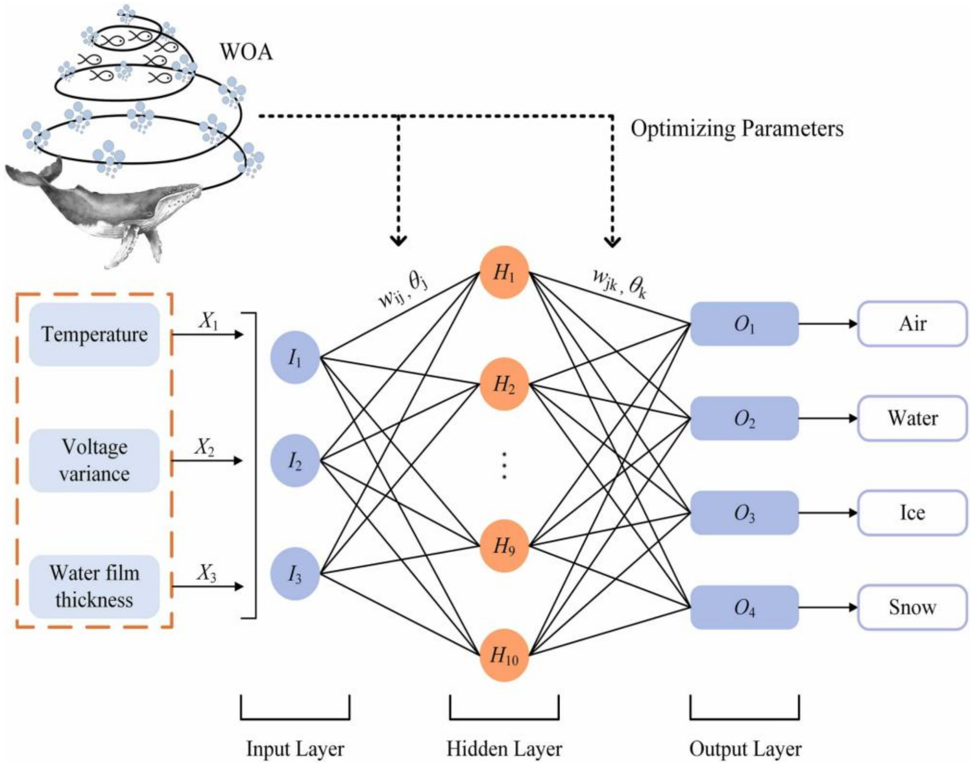

Fig. 2. A conceptual representation of the WOA-BP network

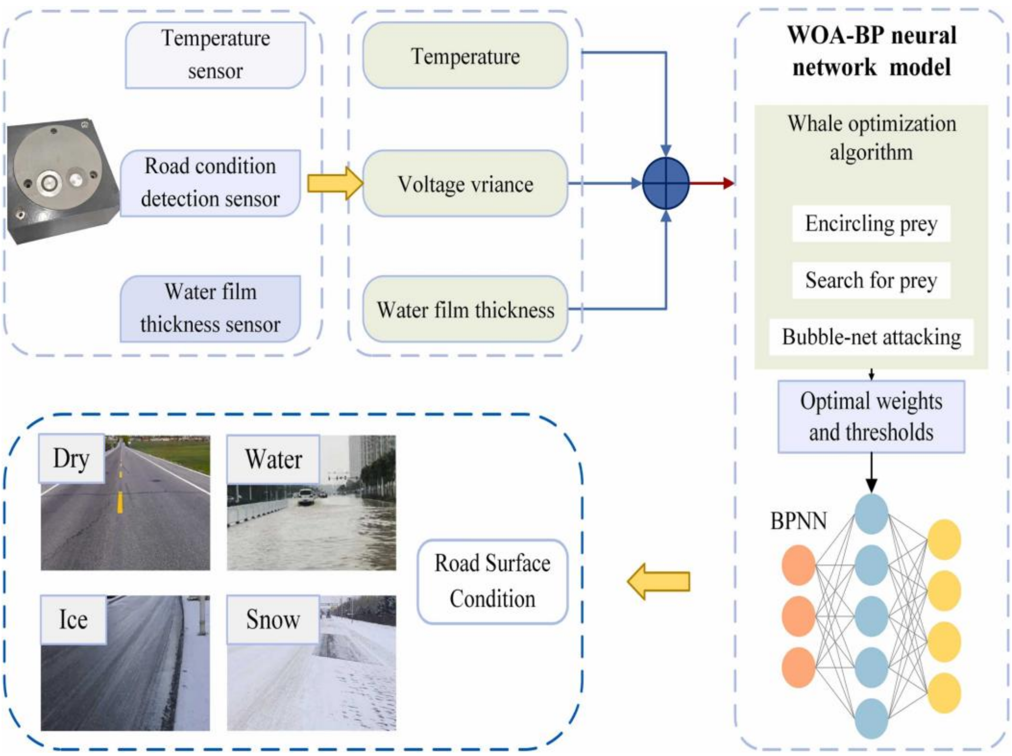

Fig. 3. System for detecting the state of road surfaces

To achieve feature-level fusion, a full feature vector is created by combining temperature, voltage variation, and water film thickness, and then this vector is fed into the trained WOA-BP neural network model. The WOA-BP neural network model determines whether the road is dry, wet, icy, or snowy based on real-time data collected from sensors and grouped into feature vectors.

IV. RESRESULTS AND DISCUSSION

Initial experiments within the temperature range of -30°C to +30°C revealed that the road condition monitoring sensor produced distinct waveform responses under dry, icy, and snowy surface states. As illustrated in Figure 4(a-b), the waveform peaks and troughs were analyzed to interpret these responses more clearly, using an average of twenty samples for voltage measurement. Figure 4(a) indicates that peak voltage responses varied across the three surface types with temperature. While dry surfaces showed minimal sensitivity to temperature changes, snow and ice exhibited more noticeable variations due to the temperature-dependent nature of their relative permittivity. However, distinguishing all three surface states based solely on peak voltage proved challenging due to overlaps.

In Figure 4(b), it is evident that in the temperature range of -30°C to 0°C, the trough voltage associated with icy conditions is noticeably different from that of dry and snowy surfaces, which appear quite similar. This suggests that using peak and trough voltages alone offers limited effectiveness for reliable classification among dry, icy, and snowy conditions.

To improve state discrimination, additional signal processing was applied to the sensor output. Voltage waveforms were sampled across different temperatures for all four surface states—dry, wet, icy, and snowy. The voltage variance was computed and scaled by a factor of 1000 to enhance clarity. As shown in Figure 4(c), within the -30°C to +30°C range, dry, icy, and snowy states showed overlapping variance patterns, particularly near 0°C. Nevertheless, temperature remained a critical parameter influencing voltage variation and, consequently, road condition assessment.

In the 0°C to 50°C range, Figure 4(d) highlights a noticeable separation between dry and wet conditions. For wet surfaces, voltage variance approached zero across all temperatures. This phenomenon is attributed to water accumulation on the sensor, causing a nearly flat voltage output. Notably, water's relative permittivity remains stable across temperature when excited at 10 kHz, resulting in a consistent waveform. Overall, voltage variance proves effective in distinguishing between dry, wet, icy, and snowy road conditions.

A. Assessment findings of the WOA-BP model

In this study, a total of 185 experimental samples were collected and divided into training and testing sets using a 70:30 ratios. To improve model performance and minimize the influence of varying units, data standardization was applied. The WOA-BP neural network was trained with 30 datasets, while its performance was evaluated using 50 datasets. The training process utilized the Levenberg–Marquardt (LM) algorithm, and 5-fold cross-validation was incorporated to prevent overfitting. The Whale Optimization Algorithm (WOA), which relies on a fitness function based on prediction error, was employed to optimize the model, as shown in Figure 5(a). During its iterations, the WOA used techniques like bubble-net foraging, prey searching, and encirclement to escape local minima. The model reached its best fitness value after 22 iterations, and Figure 5(b) illustrates the convergence of the WOA-BP neural network.

After 15 iterations, the model achieved a mean squared error (MSE) of 0.003144 on the validation set, and training was concluded after the 21st iteration upon convergence. In the test results displayed in Figure 5(c), blue triangles represent actual classifications and red dots indicate predicted outputs. Labels 1, 2, 3, and 4 correspond to dry, wet, icy, and snowy conditions, respectively. Out of 55 test samples, all predictions were accurate except for one instance, where a snowy surface was misclassified as icy. The overall classification accuracy reached 98.2%.

The confusion matrix in Figure 5(d) further confirms the model's performance, displaying actual versus predicted categories. Accuracy was 100% for dry, wet, and icy conditions, and 94% for snowy surfaces. These results indicate that the WOA-BP neural network can reliably identify various road surface conditions. Moreover, the experiment demonstrates the model's effectiveness even with a relatively small dataset of just 185 samples.

B. Comparison with alternative methodologies

Separate applications of BPNN, RF, and SVM were used to evaluate the efficacy and superiority of the suggested strategy in identifying road surface conditions. Just like the WOA-BP model, the BPNN's parameter settings were spot on. A radial basis function was the kernel function used by the support vector machine. In addition, the data was divided into training and test sets using a 7:3 ratios, which ensures that the results are reliable. Each of the three models then used the dataset for training and evaluation. Confusion matrices and total accuracy rates were used to assess the models' performance.

Figure 6 shows the outcomes of the three approaches' experiments. With an overall accuracy of 90.9%, the BPNN accurately identified dry, wet, and icy conditions, however it incorrectly classified 31% of snow samples as ice, as shown in Figure 6(a). The SVM performed suboptimally, as shown in Figure 6(b). It achieved an overall accuracy rate of 87.3% but only 83% for ice and 45% for snow. As shown in Figure 6(c), the RF model achieved a total accuracy of 92.7% by incorrectly identifying 7% of ice as snow and 16% of snow as ice. The WOA-BP model thus outperformed the other two approaches in terms of the accuracy of road surface condition detection.

Each of the four approaches underwent fifteen iterations of testing to ensure the model was stable. The results of detecting the state of the road surface using each of the four approaches are shown in Figure 6(d-e). Among the four states—dry, wet, icy, and snowy—the WOA-BP model had the best overall accuracy, with a peak accuracy of 100% and an average recognition accuracy of 98.8%. While the WOA-BP model achieved an average accuracy of 93.2%, the RF and SVM only managed 92.9% and 81.3%, respectively. Due to the large amount of data often needed by an RF model to achieve ideal performance, it performed poorly in this experiment. A support vector machine (SVM) model works well with small samples but struggles with multi-classification problems.

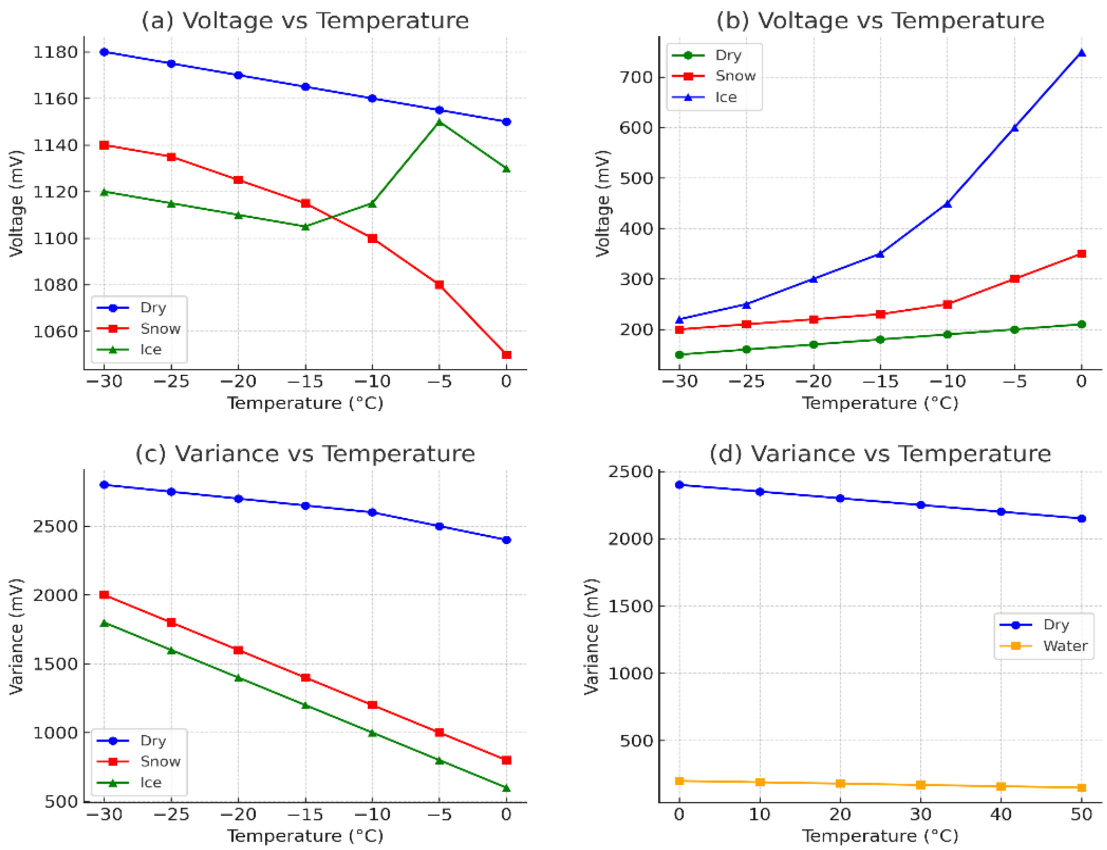

Fig. 4. The road condition detection sensor's response at 10 kHz under different surface conditions. (a) Sensor peak voltage output at different temperatures under dry, icy, and snowy conditions; (b) Sensor valley voltage output at different temperatures; (c) Sensor output voltage variation under dry, icy, and snowy conditions; (d) Sensor output voltage variation under dry and wet conditions.

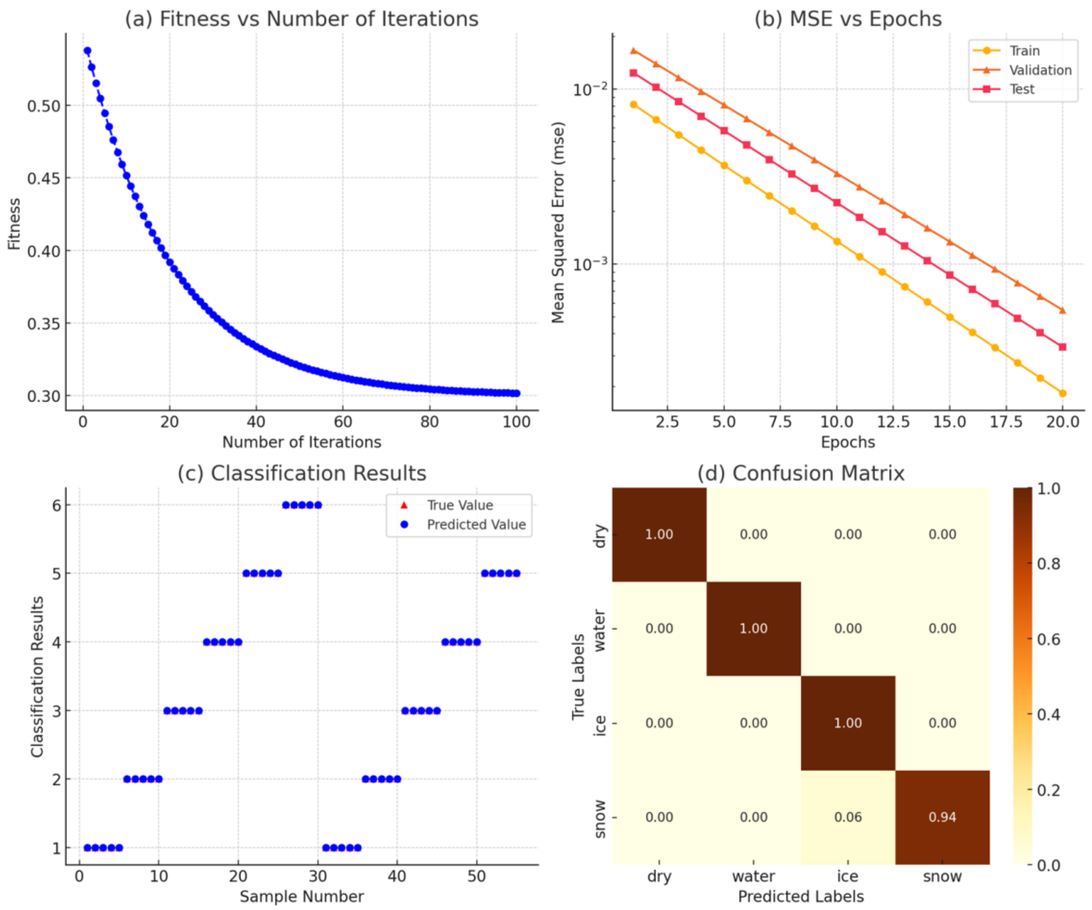

Fig. 5. Assessment outcomes of the WOA-BP neural network. (a) Iterative procedure of the WOA; (b) Convergence trajectory of the WOA-BP neural network; (c) Forecasted outcomes for the test set; (d) Confusion matrix of the WOA-BP neural network applied to the test set

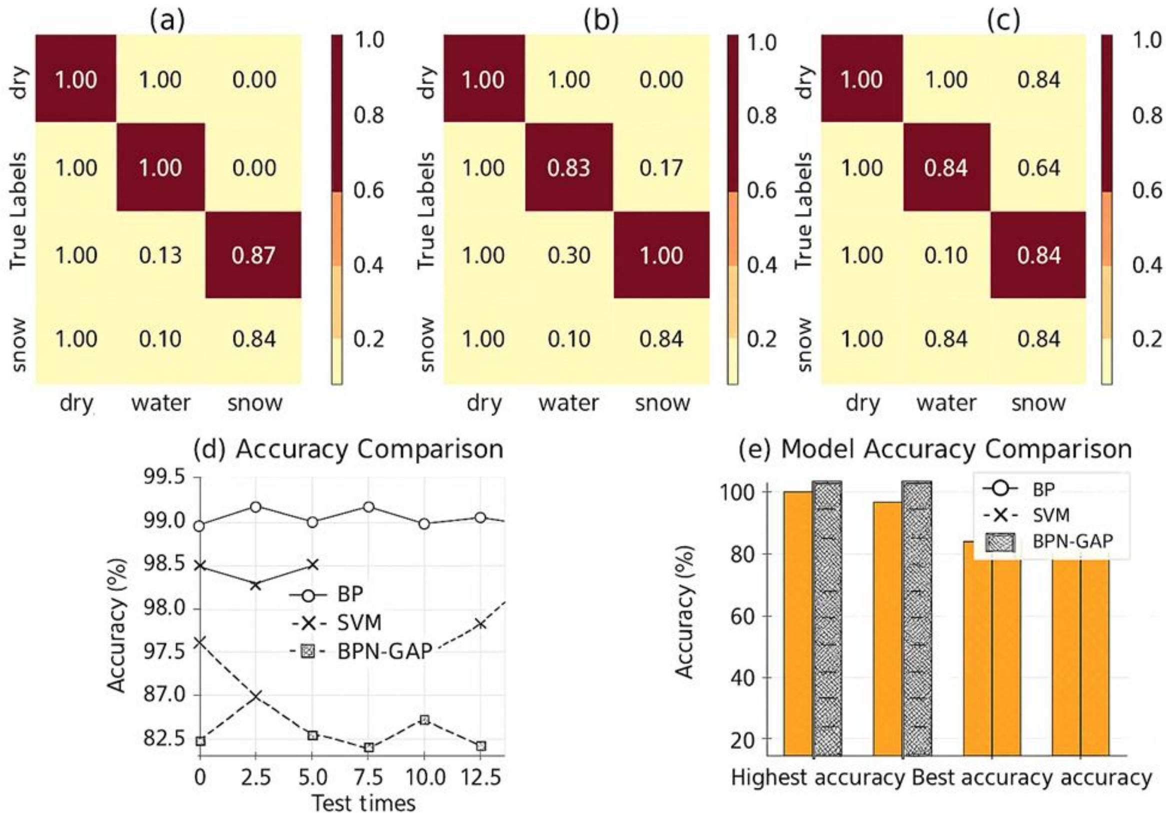

Fig. 6. Proposed method vs. machine learning. (a) BPNN confusion matrix; (b) SVM confusion matrix; (c) RF confusion matrix; (d) A comparison of the accuracy of the four algorithms after 15 tests; (e) Accuracy statistics

The BPNN outperforms RF and SVM in terms of performance. However, BPNN's performance becomes unstable due to its tendency to converge to local minima, resulting in an average accuracy of only 93.2%. Improvements to the BP neural network, efficient multisensor data fusion, and new feature selection are responsible for the high accuracy of road surface condition classification in this study. The raw voltage signals from capacitive road sensors were not used for feature selection; instead, the variance of the data was estimated. As a foundation for future classification, this processing method greatly enhanced the disparities among various road conditions. With the goal of enhancing both WOA's global search capabilities and BPNN's robust classification performance, the WOA-BP neural network was created. By modifying the BPNN's initial weights and thresholds, WOA improved prediction performance and resilience while reducing the impact of local op-tima. In addition, three different kinds of sensors were used to collect data from the road surface, and the WOA-BP neural network allowed for the combination of data from several sensors, which overcame the shortcomings of each sensor. In particular, the WOA-BP neural network was fed a full feature vector encompassing attributes like temperature, voltage fluctuation, and water layer thickness in order to perform feature-level fusion. The accuracy and robustness of identifying road surface conditions were both significantly improved by this approach. Finally, there is substantial technical support for improving driving safety and expanding intelligent transportation systems offered by the proposed low-cost, high-accuracy method for identifying road surface conditions.

V. CONCLUSION

By integrating the WOA-BP neural network with an ensem-ble of road condition sensors, this study introduces a road condition detection system that significantly enhances detection accuracy. Using BPNN for data fusion, this detection technique gathers data on road surface conditions from three different types of sensors. This method greatly improves the detection system's accuracy and reliability by achieving information optimization and complementarity, which successfully addresses the environmental susceptibility linked to a single sensor source. To solve the issue of BPNN becoming stuck in local minima, we used WOA to adjust the BPNN's initial weights and bias thresholds. This improved the model's convergence rate and classification performance significantly. Furthermore, results from the created testing equipment show that capacitive sensors' output signal is significantly affected by temperature changes in a variety of road conditions (dry, wet, icy, snowy). As a result, the model's identifying performance can be improved by making voltage variation the main property for differentiating different road scenarios. In a performance validation conducted across a temperature range of -30°C to 50°C, the WOA-BP model outperformed BPNN, SVM, and RF, achieving an average accuracy rate of 98.8% and a maximum accuracy rate of 100% in classifying dry, wet, icy, and snowy road conditions. The model also demonstrated improved detection accuracy and model stability. Improving road condition detection is essential for making roads safer, and this study presents a new method that does just that.

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