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Original Article

Real-Time Black Ice Detection in Hilly Areas Using LoRa and IoT Network with a Machine Learning Algorithm

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***Abstract* - *Black ice is a serious road safety hazard, especially in cold and high-altitude areas, as it often forms silently and invisibly. Drivers often remain unaware of black ice until it's too late, leading to sudden and dangerous situations on the road. That's why accurate and timely detection is essential to help prevent accidents and support effective traffic management. This research presents an intelligent black ice detection system that combines environmental sensors and a deep learning-based vision model. The system monitors critical weather parameters, temperature, humidity, dew point, wind speed, wind direction, and precipitation using real-time sensors, and classifies road conditions (dry, wet, saline, snow) using a trained ResNet101 model. A custom logic engine analyses sensor data and image predictions to determine the presence of black ice. The model achieved an accuracy of 95.6% and was validated using both Grad-CAM visualizations and confusion matrix analysis. Hardware implementation using LoRa network-enabled sensor nodes and a gateway, with integration of LoRa and Wi-Fi interfaces, enabled practical deployment. The results demonstrate that integrating sensor and vision systems enhances the reliability of black ice detection, offering significant potential to improve road safety during extreme winter conditions.*

Keywords* - *Black Ice Detection, IoT-based Monitoring, Multimodal Sensing, ResNet101, Road condition classification.

1. Introduction

Black ice is a risk for drivers, especially in cold and hilly areas where black ice formation is very quick and quite hard to see, which can cause accidents. Black ice is one of the most dangerous winter weather hazards for roads because it's nearly invisible and forms quickly. Unlike snow or visible frost, black ice is just a thin layer of ice that forms on asphalt without changing how the road looks, making it very hard for drivers to see and avoid. [1]. Black ice usually forms on roads when different weather conditions like temperature, humidity, rain or snow, wind, and the state of the road surface come together [2, 3]. Most current methods for spotting black ice use remote weather stations or complicated computer models with complex GIS tools. But these systems can be expensive, slow and not easy to move, which makes them less useful in rural or mountain regions where quick and simple solutions are needed.

This study predict the formation of black ice and generate the alerts accordingly and communicate the alerts with LoRa and this research is done because recent studies have shown that the accidents due to the black ice formation on roads are comparatively much higher than the common winter road conditions, especially during the early morning hours when both air and road surface temperatures are at their lowest [4] Between December 24 to January 20, a significant number of ice-related accidents were reported in Himalayan region especially around Manali in Himachal Pradesh, the hilly roads of Uttarakhand, and the Kashmir Valley black ice poses a serious threat to road safety during winter. The Manali Keylong route, near the Atal Tunnel, often experiences black ice in the early morning and evening, making driving extremely dangerous. In December, authorities issued warnings advising people to avoid this route during those times. Similarly, high-altitude roads in Uttarakhand, like those near Chopta, Kedarnath, and Joshimath, frequently see accidents due to vehicles skidding on black ice. In Kashmir, roads from Srinagar to Gulmarg and Sonamarg are often closed or subject to travel warnings during cold spells because of black ice. These situations underscore the urgent need for real-time, local black ice detection systems across the mountainous regions of northern India, emphasising the necessity for reliable early warning systems to mitigate such incidents. Most of these accidents happened before dawn, when humidity was near saturation and temperatures were around or below 0°C [5]. Over the years, research on predicting and reducing the dangers of black ice has focused heavily on using weather and location-based models. These models often rely on tools like GIS and simulation software to improve forecasting [5] made a major contribution was made by developing a model that combines system dynamics with DNNs to find important factors like road temperature and moisture, helping improve road safety [5, 11]. While this method is accurate and detailed, it requires large datasets and complex tools like Powersim Studio and a strong GIS setup. This makes it less practical for simpler or embedded systems that need more lightweight solutions.

In response to these limitations, this study proposes a low-cost, real-time embedded hardware system for dew point monitoring and road condition classification to aid in black ice risk detection. The dew point is a critical indicator, as black ice is likely to form when the road surface temperature falls to within 1.5 °C of the dew point, particularly under high humidity conditions. By combining temperature, humidity, wind, and precipitation sensors with a camera-based surface condition classifier powered by a ResNet-101 convolutional neural network, the proposed system aims to provide a practical and deployable solution for on-road black ice detection. This research builds upon the foundational principles of multi-sensor black ice validation presented by [4], but diverges in implementation by focusing on embedded, standalone, and real-time hardware-level monitoring. This direction not only reduces system complexity and cost but also enhances portability, making it suitable for smart vehicles, roadside units, or remote weather stations.

1.1. Research Gap

Existing black ice detection systems often rely exclusively on weather-based forecasting or computationally intensive models that are not feasible for embedded or edge devices, leaving a gap that has not been addressed by hybrid multi-models. Current systems depend upon road images, a car-mounted camera-based system or an individual sensor-based system. These methods typically lack real-time, on-site alert capabilities and overlook the potential of combining sensor data with visual road analysis. Furthermore, there is a notable gap in the literature regarding practical, deployable hybrid systems that seamlessly integrate deep learning algorithms with IoT-based environmental sensors for real-time black ice detection in challenging terrains.

1.2. Problem Statement

The detection of black ice remains a very important and unresolved issue, starting from the parameters involved in the formation of black ice on roads, which result from the interaction of various factors, including temperature, humidity, dew point, road surface conditions, and wind speed. Existing technologies, such as static warning systems, temperature and humidity sensors, and dew point calculators, frequently exhibit limited effectiveness as they function in isolation, failing to account for the comprehensive array of environmental variables. In addition, these systems demand substantial computational resources and capacity, consequently yielding generalized or postponed alerts that fall short of the accuracy required for immediate and localized detection. Additionally, such systems incur considerable costs in terms of implementation and maintenance across extensive road networks, thereby constraining their scalability so is a need for a lightweight, deployable system that can detect black ice by using environmental conditions and image classification which is capable of operating in remote and harsh conditions and majorly a cost-effective and hybrid multimode solution needed to this problem.

1.3. Objective

The objectives of this research are defined to address these requirements through an integrated, intelligent, and deployable solution.

- To develop an intelligent black ice detection system by integrating environmental sensors with a deep learning-based vision model for hybrid decision making.
- To accurately classify road surface conditions (dry, wet, saline, snow) and detect potential black ice formation using real-time sensor inputs and camera-based predictions.
- To validate the model performance using Grad-CAM and confusion matrix analysis, achieving high classification accuracy.
- To demonstrate the system's practical deployment through a hardware prototype incorporating LoRa network-enabled sensor nodes and a gateway unit with LoRa-Wi-Fi integration for data transmission.

1.4. Manuscript Organization

Section 2 gives an overview of past research related to black ice detection, road condition monitoring, and the use of multiple types of sensors. Section 3 explains the proposed system, showing how environmental sensors and a deep learning model work together. Section 4 describes how the hardware, such as sensor nodes and the central gateway, was built and how the data is processed. Section 5 shares the results, showing how well the system works using real-world data and visuals. Finally, Section 6 wraps up the study and suggests ideas for future improvements.

2. Literature Review

Over the past 20 years, black ice detection has improved significantly. This section aims to review the different techniques employed in black ice detection and analysis, emphasising their individual contributions to advancing knowledge in this area. Many studies have looked into black ice, and they have partly explained what causes it to form. It has evolved from basic methods based on fixed temperature and humidity limits to advanced techniques using deep learning and sensor fusion. Accurately and quickly detecting black ice is crucial for reducing winter road accidents [3], especially in high-risk areas like mountain roads where such hazards are more common, so researchers from different regions of the globe use different approaches to solve the black ice problem.

2.1. Sensor-Based Detection Approaches

Over the past two decades, sensor-based approaches for black ice detection have evolved from simple threshold-based systems to more dynamic and responsive models. For instance, [5] developed a black ice prediction model that integrates system dynamics with deep neural networks, utilising meteorological inputs such as temperature, humidity, and precipitation, along with GIS-based spatial analysis. This model could effectively identify high-risk areas, especially in regions like Korea. However, its reliance on extensive computing resources and large datasets restricts its practical and real-time deployment. Other studies, like [10], proposed real-time warning systems using humidity and temperature sensors embedded in highways [6]. These systems offer quick responses but often lack integration with visual or contextual data, limiting their detection accuracy.

2.2. Image-Based and Vision Systems

Recent advancements in computer vision have enabled the use of Convolutional Neural Networks (CNNs) for detecting black ice in road images. [7] utilized CNNs in autonomous driving environments to distinguish between icy and non-icy surfaces, while [8] developed a 1D CNN model leveraging mmWave backscattering data to detect icy conditions without relying on cameras. [9] Further explored segmentation models under varying weather conditions and demonstrated that deep learning models can generalize well with diverse datasets. Despite so many advantages, these kinds of models require significant computational power, which makes them challenging to deploy on embedded systems.

2.3. Hybrid and Multimodal Systems

A growing trend involves combining sensor and vision data to enhance detection accuracy [14]. Used sensor data from test roads in Alberta to forecast road surface temperatures, and [15] developed a simulation framework mapping black ice risk using terrain, layout, and crash data. These methods offer comprehensive insights but remain largely simulation-based. Their practical deployment is limited due to complexity, infrastructure requirements, or lack of support for low-power operation support.

2.4. Road-Embedded and Vehicle-Based Systems

Studies like [12] demonstrated that vehicle-mounted sensors can predict night-time icing using real-time temperature and weather data, making them valuable for driver alerts. Similarly, [13] used crash and weather data with machine learning to predict black ice risk. While practical and responsive, these methods often depend on vehicle-specific hardware or centralized processing, making wide-scale deployment in rural or hilly areas less feasible.

2.5. Critical Summary of Literature

From the review above, it is evident that although substantial progress has been made in black ice detection, many existing systems either rely heavily on infrastructure, are computationally expensive, or fail to combine multiple data sources in a lightweight, deployable manner. Few studies attempt to fuse real-time environmental sensor data with deep learning-based visual analysis on embedded hardware platforms.

Moreover, most systems are not optimized for use in geographically complex areas such as the rural and upper Himalayan parts of India. To overcome this limitation, the current research introduces a unique, cutting-edge, and financially sustainable hybrid multimodal system that synthesizes temperature, humidity, wind, and precipitation sensors with a ResNet101-supported road surface classification algorithm [37]. This hybrid model is designed for real-time inference, wireless communication via LoRa, and deployment in regions like Manali, Uttarakhand, and Kashmir. Unlike previous approaches, this system emphasizes portability, processing, and the fusion of vision and environmental sensing, ensuring higher accuracy and better adaptability in resource-constrained, high-risk areas.

3. Methodology and System Architecture

This study introduces a hybrid black ice detection system that brings together real-time environmental monitoring through sensors and road surface classification using a deep learning model. As shown in Figure 1, the approach follows the order of process where sensor data and camera inputs work together to assess road safety conditions more accurately and real-time.

Unlike traditional black ice detection systems that primarily depend on centralized weather forecasting stations, satellite imagery, or high-cost radar and GIS-based simulation tools, the proposed study presents a deployable, low-cost, and real-time solution tailored for remote and hilly terrains. Prior works such as [6] focused on either vision-based classification or environmental sensors in isolation, often without real-time decision-making capabilities. In contrast, this research introduces a hybrid architecture that intelligently fuses environmental sensor data (temperature, humidity, dew point) with visual surface analysis using a pre-trained ResNet101 model. This combination enables not only higher detection accuracy (95.6%) but also practical field deployment through a LoRa-based IoT framework. Furthermore, while earlier studies have largely remained at the simulation or laboratory stage, this work advances the field by validating the system on hardware prototypes in real-world Himalayan conditions. The integration of machine learning with embedded systems and long-range wireless communication represents a novel, scalable approach that has not been previously demonstrated in the existing literature.

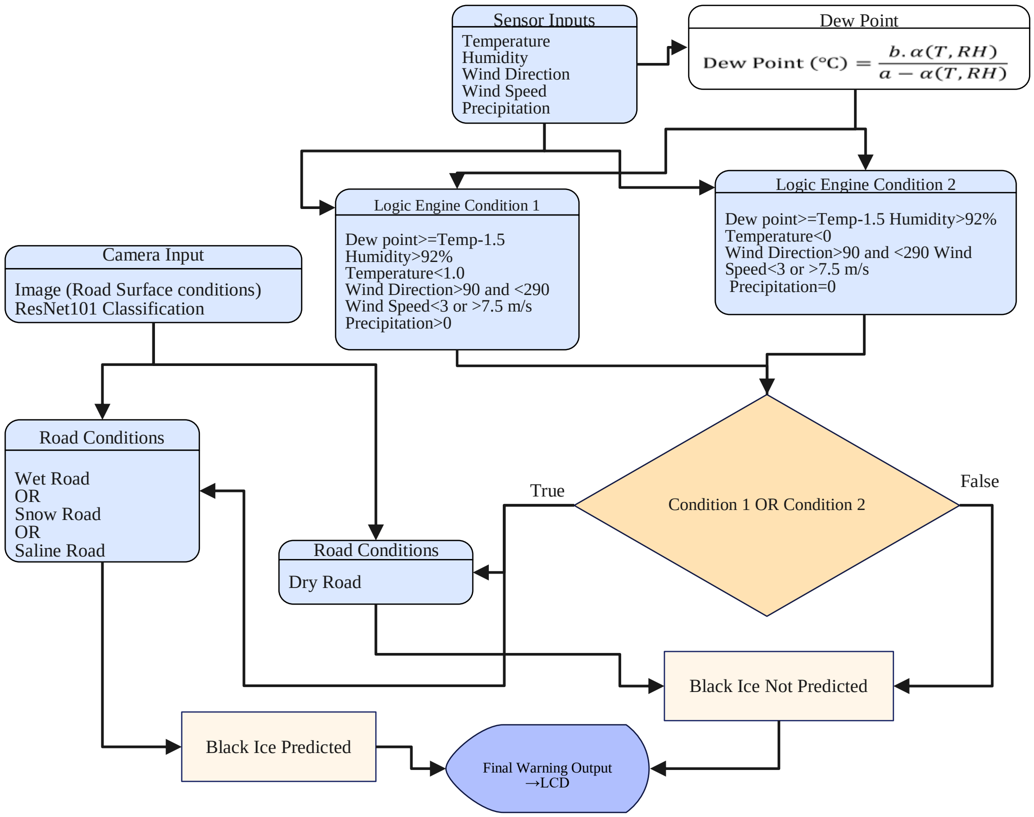

Fig. 1 Overview of black ice condition evaluation engine

The first stage focuses on system design and setup. This is where the study defines the area and carefully selects the parameters which is responsible for black ice formation, like temperature, humidity, wind speed/direction, and precipitation, alongside how the condition of the road affects. At this stage, the study establishes the data collection strategy and designs the algorithm. The system uses a deep learning model to classify road conditions and train the model for the different conditions of road as shown in Figure 2, where images of road surfaces were used to train the ResNet101-based classifier [18], representing four distinct conditions: Dry, Wet, Saline, and Snow. These categories are the core of the vision-based module for identifying road conditions [19] in the proposed black ice detection framework. This foundational step builds a bridge between raw sensor inputs and the computer vision pipeline that interprets road conditions.

In phase 2, the system springs into action with real-time data acquisition and processing. It continuously gathers atmospheric and road surface data, computes dew point values using the Magnus approximation formula [20] and evaluates the probability of black ice through preset thresholds. The dew point plays a crucial role in black ice formation, as it marks the temperature at which moisture in the air condenses onto surfaces, potentially leading to ice under the right conditions. It is calculated using the Magnus approximation, which estimates the dew point based on temperature and humidity in percentage as shown in Equation (1) [20]. The formula uses the nonlinear function α(T, RH), which incorporates the natural logarithm of relative humidity and temperature terms, and is expressed as:

$$T_{d=}\frac{b.\alpha(T,RH)}{a-\alpha(T,RH)} \quad (1)$$

The dew point is determined based on a derived function of temperature and humidity, with two empirical constants: a = 17.27 and b = 237.7°C as shown in Equation (2). In this formula [20], T represents the ambient temperature in degrees Celsius, and RH denotes the relative humidity in percentage [38]. The resulting dew point value helps identify whether surface conditions are conducive to condensation.

$$\alpha(\mathrm{T,RH}) = \frac{\mathrm{a.T}}{\mathrm{b+T}} + \ln\left(\frac{\mathrm{RH}}{100}\right) \quad (2)$$

Table 2 presents a representative set of environmental and visual conditions used to validate the black ice detection logic.

Each row corresponds to a specific observation, during which key parameters such as dew point, humidity, precipitation, temperature, wind direction, and wind speed were monitored using the deployed sensor node. These values were assessed using a rule-based logic engine to determine whether the atmospheric conditions met the threshold for black ice formation [4]. A critical logic trigger is defined by the dew point being within 1.5°C of the ambient temperature, relative humidity exceeding 92%, and wind speeds falling below 3 m/s or above 7.5 m/s within a directional window of 90° to 290°. The presence or absence of precipitation further influences the likelihood of ice formation. When these sensor conditions are met, and the ResNet101-based image classifier simultaneously detects wet, saline, or snow-covered roads, the system issues a black ice formation detected warning. Conversely, if the image classifier detects a dry road or if key conditions are not satisfied, the system refrains from issuing an alert.

The study uses a simple but important rule, "Dew Point ≥ Temperature - 1.5°C" [21] as shown in column 1 of Table 2. If the dew point is within 1.5°C of the air temperature, there's a good chance that moisture in the air could settle on the road. When it's also cold enough, especially near freezing, this moisture can quickly turn into black ice [4], which is thin, hard to see, and very dangerous. By including this condition in detection logic, the system produced an alert warning of the early signs of black ice, helping to improve road safety before things get risky. A critical logic trigger is defined by the dew point being within 1.5°C of the ambient temperature, relative humidity exceeding 92%, and wind speeds falling below 3 m/s or above 7.5 m/s within a directional window of 90° to 290°. The presence or absence of precipitation further influences the likelihood of ice formation [22]. When these sensor conditions are met, and the ResNet101-based image classifier simultaneously detects wet, saline, or snow-covered roads, the system issues a Black Ice Formation Detected warning.

Table 1. Comparison of the proposed system with existing black ice detection methods

Study / Method	Data Type	Approach	Real-Time Capability	Deployment	Accuracy	Communication Protocol
[11, 12]	Environmental Sensors	Temperature + Humidity Threshold	No	Simulated	Not Reported	None
[1]	Camera-Based (Image only)	Image classification using CNN	Partial (cloud-based)	Lab Test	90.2%	Wi-Fi
[4]	Sensor + GPS	Sensor Fusion + GIS Overlay	No	Simulated	88.7%	GSM
[13]	Sensors Only	Weather-Based Rule Engine	Yes (Edge device)	Field Tested	91.4%	Zigbee
This Study	Image + Environmental Sensors	Hybrid Model (ResNet101 + Rule Engine)	Yes (Edge + LoRa)	Field deployed (Himalayas)	**95.6%**	**LoRa**

Dry Condition | Wet Condition | Saline Condition | Snow Condition

Fig. 2 Road condition classification using CNN

Table 2. Sensor data with visual classification, triggering alerts based on set thresholds and confirmed image analysis

Dew Point	Humidity	Precipitation	Temperature	Wind Direction	Wind Speed	Vision Detection	Warning
Dew Point >= Temp - 1.5	>92%	>0	<1.0	>90, <290	<3 or >7.5 m/s	Wet road	Black Ice Predicted
Dew Point >= Temp - 1.5	>92%	0	<0	>90, <290	<3 or >7.5 m/s	Wet road	Black Ice Predicted
Dew Point >= Temp - 1.5	>92%	>0	<1.0	>90, <290	<3 or >7.5 m/s	Dry road	Black Ice not Predicted
Dew Point >= Temp - 1.5	>92%	0	<0	>90, <290	<3 or >7.5 m/s	Dry road	Black Ice not Predicted
Dew Point >= Temp - 1.5	>92%	>0	<1.0	>90, <290	<3 or >7.5 m/s	Snow road	Black Ice Predicted
Dew Point >= Temp - 1.5	>92%	0	<0	>90, <290	<3 or >7.5 m/s	Snow road	Black Ice Predicted
Dew Point >= Temp - 1.5	>92%	>0	<1.0	>90, <290	<3 or >7.5 m/s	Saline road	Black Ice Predicted
Dew Point >= Temp - 1.5	>92%	0	<0	>90, <290	<3 or >7.5 m/s	Saline road	Black Ice Predicted

Conversely, if the image classifier detects a dry road or if key conditions are not satisfied, the system refrains from issuing an alert. This fusion of environmental sensing with machine learning-based image classification enhances the reliability of the detection model [23], thereby reducing false positives and increasing safety in real-world deployments. The system demonstrates improved resilience to false positives by integrating camera-based surface detection. For example, in rows 3 and 4 of Table 2, despite sensor readings indicating possible black ice conditions, the classifier confirmed a dry road surface, leading the system to correctly suppress a black ice warning. This cross-validation mechanism helps avoid over-alerting and enhances decision confidence. Overall, the combination of environmental thresholds and visual confirmation provides a more robust and context-aware approach to black ice detection, particularly in complex weather conditions where rule-based logic alone may lead to misclassification.

Finally, the third stage focuses on system output, visualization, and validation. Real-time alerts are shown on an LCD, and all sensor readings and predictions are stored for post-analysis. Validation is done by comparing predicted conditions with actual field observations or external weather data [25]. While advanced statistical validation methods are beyond the current scope, the system's modular design allows for future integration of time series analytics, remote dashboards, or cloud-based logging to enhance long-term performance evaluation.

3.1. IoT Framework for Data Collection and Monitoring

To make real-time black ice detection possible in outdoor and often remote areas, this study introduced a custom hardware setup that includes a sensor unit and a central gateway. The sensor unit collects key environmental data, including temperature, humidity, rainfall, wind speed, and wind direction [24], all of which play a significant role in black ice formation. This data is then sent wirelessly using a LoRa communication module to the central gateway [26].

There, it's combined with camera-based road condition analysis to give a full picture of the situation. For this, the dataset used for training and evaluation consisted of approximately 2,400 labeled images, equally distributed across four road surface conditions: dry, wet, saline, and snow, with about 600 samples per class. Samples were acquired from various high-altitude regions. In order to achieve robustness and generalizability, data gathering took place at separate time intervals (morning, afternoon, and evening) [17] and across a range of lighting and meteorological conditions. At the same time, environmental sensor indicators (temperature, humidity, dew point, and precipitation) were thoroughly recorded and coordinated with the imaging data to accurately illustrate the contextual landscape of each surface condition. This variety in geographic and environmental conditions helps improve the model's ability to generalize across different scenarios, which is critical for deployment in other hilly or remote areas. The system is designed to use low power, cover long distances, and smoothly integrate both sensor readings and visual inputs, making it ideal for places like mountains or rural roads where black ice is common and dangerous because the integration of IoT enables seamless connectivity between physical devices and digital platforms, facilitating real time data exchange and decision making across distributed environments [16]. Relevant to black ice formation, including temperature, humidity (DHT11), precipitation (rain sensor), and wind speed (anemometer) and wind direction, with data transmission via LoRa. The sensor node in Figure 3 is responsible for acquiring critical environmental parameters such as air temperature, relative humidity, precipitation intensity [27], and wind speed, all of which influence black ice formation. The circuit is built around a microcontroller, which reads inputs from:

- A DHT11 sensor to measure temperature and humidity.
- A rain sensor to detect the presence of precipitation.
- An anemometer to capture real-time wind speed.
- Wind Vane Sensor 360 for wind direction.

These sensor readings are transmitted using a LoRa (Long Range) transceiver module [26], which ensures low-power, long range wireless communication, suitable for remote or mountainous deployment scenarios. The node operates on a 5V regulated supply and is optimized for low energy consumption in the field.

The gateway node Figure 4 acts as the central receiver and decision-making unit. It uses another microcontroller to collect data from the sensor node via LoRa. The received data is then forwarded to a NodeMCU module [28], which handles logic evaluation and real-time road conditions. Classification results obtained from the camera.

The gateway is equipped with an I2C-based LCD module that displays:

- The current road surface classification (Dry, Wet, Saline, Snow).
- A black ice warning is issued if environmental conditions match critical thresholds.

The modular design of the gateway ensures it can be easily extended to cloud-based logging or mobile app alerts in future deployments. To support efficient and accurate black ice detection, a study shows the development of a hybrid IoT framework that brings together wireless sensors and edge-based vision systems. Each sensor node monitors key environmental factors like temperature, humidity, wind speed and direction, and precipitation [39]. It also includes a camera module that uses a ResNet101-based model to classify road surface conditions. These nodes are involved in wireless communication utilizing low-power LoRa technology, which allows for extensive data transmission over substantial distances with trivial latency and diminished energy usage.

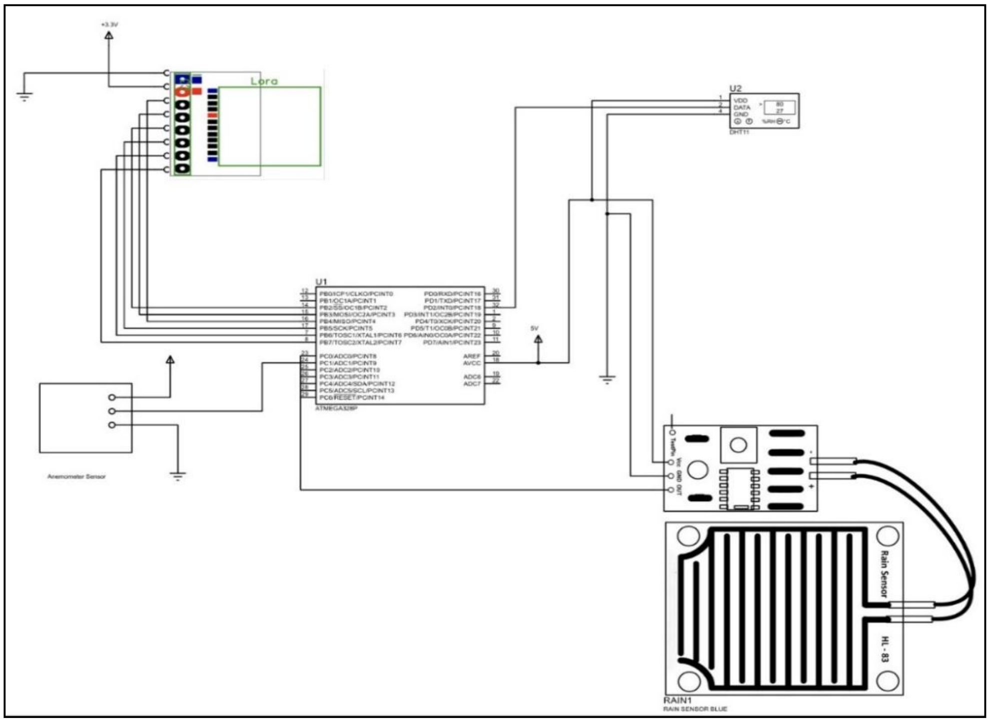

Fig. 3 Circuit diagram of the sensor node used for capturing environmental parameters

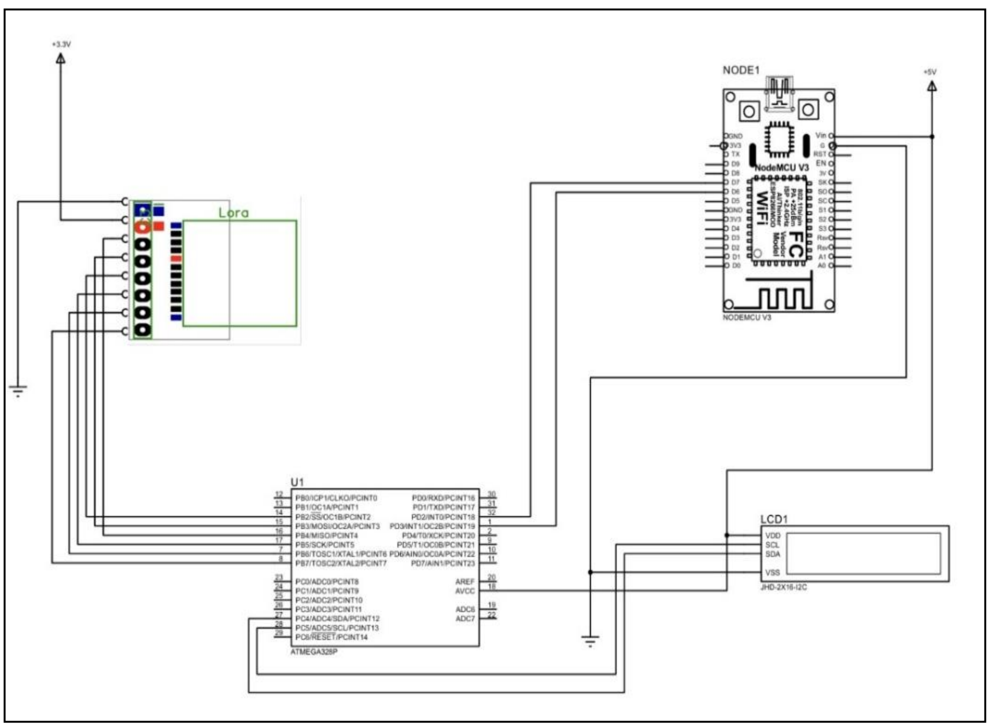

Fig. 4 Gateway circuit diagram used to collect and display data from remote sensor nodes

As shown in Figure 5, all sensor nodes send their data to a central LoRa-WiFi gateway. This gateway collects and forwards the information to a cloud platform for real-time monitoring and analysis. The system is smart enough to run basic data fusion and image processing directly on the device, reducing reliance on the cloud and enabling faster responses to dangerous road conditions. The system operates effectively even in challenging environments, such as hills or icy roads, ensuring continuous data flow, rapid detection, and timely black ice alerts through its combination of sensor and camera inputs.

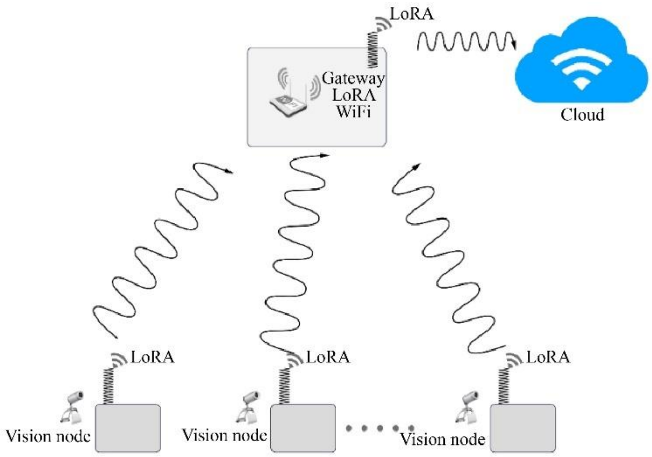

Fig. 5 IoT-based LoRa sensor network with integrated vision nodes for environmental monitoring and black ice detection

All environmental sensors, including temperature, humidity, and rain detection modules, were calibrated prior to deployment. Calibration was performed using manufacturer-supplied reference values and cross-checked against standard meteorological instruments for accuracy. Temperature sensors were verified within ±0.5°C accuracy using a certified thermometer under controlled conditions. Humidity and dew point sensors were tested in a chamber with controlled moisture levels to ensure consistency. Each sensor module was also tested across a range of conditions before final deployment in the field.

4. Implementation

The proposed black ice detection system was constructed using a modular, distributed setup comprising a sensor node and a gateway unit, both powered by low-energy microcontrollers and connected via long-range wireless communication. This setup enables real-time collection of both environmental data and road surface images. As shown in Figures 5 and 6, the sensor node has various modules to measure temperature, humidity, wind speed, direction and precipitation. This environmental data is wirelessly transmitted via a LoRa module to the gateway unit, where it is analyzed by a logic engine working in tandem with a ResNet101-based image classifier. Together, they evaluate the risk of black ice formation based on predefined thresholds. Figure 8 outlines the decision-making logic used by the system to determine when a black ice warning should be triggered based on a combination of weather data and visual road condition analysis.

4.1. Sensor Node Hardware

The sensor node in Figure 6 was designed to collect real-time environmental data that can contribute to the formation of black ice. It includes a rain sensor to detect how wet the road is, and an anemometer to measure wind speed, both of which play important roles in freezing conditions [41]. A 360° wind vane captures wind direction to help understand airflow patterns that can speed up or slow down road surface cooling [40]. For accurate surface monitoring, an IR temperature sensor checks how cold the road is, which is key to spotting freeze risks. A microcontroller manages all sensor operations and data collection, while a LoRa module ensures that the information is sent wirelessly over long distances to the central gateway for further analysis [42]. The entire node is powered via a regulated 5V supply and is optimized for energy efficiency to support continuous operation in remote field environments.

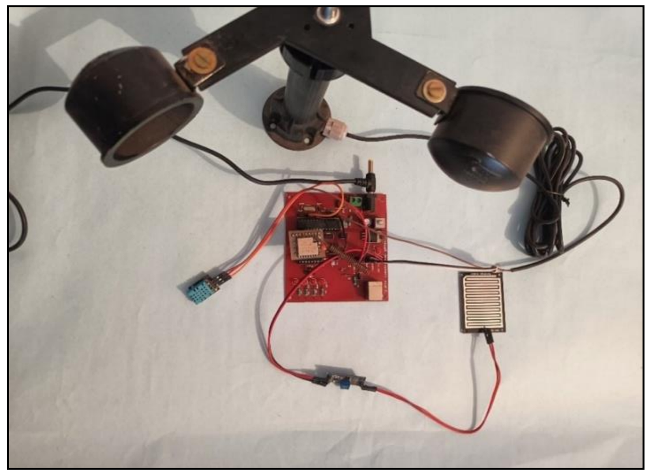

Fig. 6 Fully assembled sensor node with integrated sensors and LoRa transmitter for environmental data collection related to black ice formation

4.2. Gateway Node and Fusion Logic

The gateway node, as shown in Figure 7, serves as the central receiver and processing unit. It performs logic evaluation based on sensor input and combines this with image-based classification from a connected camera module. Key hardware elements of the gateway unit include a LoRa receiver module, which captures transmitted data packets from remote sensor nodes for centralized processing [29].

A microcontroller is responsible for managing the initial decoding of this data and routing it appropriately within the system. The NodeMCU module handles logic computation and decision making, executing the threshold-based conditions required for black ice detection. For user interaction, an I2C-based LCD display is integrated to provide real-time feedback on the detected road surface type and issue black ice warnings when conditions are met [30]. The gateway evaluates a set of rule-based thresholds on the basis of air temperature, air humidity and other factors [31] to determine if conditions are conducive to black ice. If dew point is within 1.5 °C of ambient temperature, relative humidity is >92%, surface temperature is near or below 0 °C, and wind speed falls below 3 m/s or above 7.5 m/s within a wind direction window of 90°–290°, the system proceeds to analyze road conditions through the camera classifier if the road is detected as wet, saline, or snow-covered, a black ice warning is issued.

5. Results and discussion

This section outlines the implementation results and performance evaluation of the proposed black ice detection system, which combines multi-sensor data with deep learning-based image classification. The system was tested under both controlled and semi-realistic weather conditions to evaluate its effectiveness in predicting potential black ice formation. Assessments were carried out for both hardware functionality and software accuracy, using a dataset of over 2000 labelled road images, approximately 500 for each category [17], and for 70-30 ratio was used for training and testing and real-time sensor readings. The ResNet101 model was trained and validated over 10 epochs, with its performance evaluated using standard classification metrics, including accuracy, precision, and a confusion matrix.

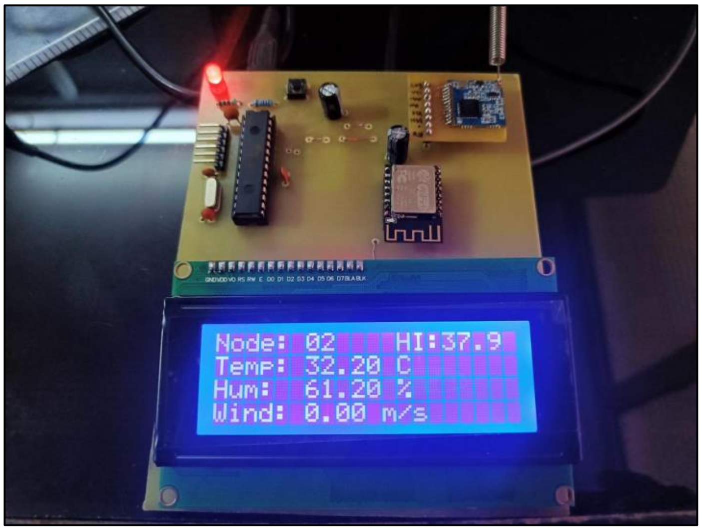

Fig. 7 Fully assembled sensor node with integrated sensors and LoRa transmitter for environmental data collection related to black ice formation

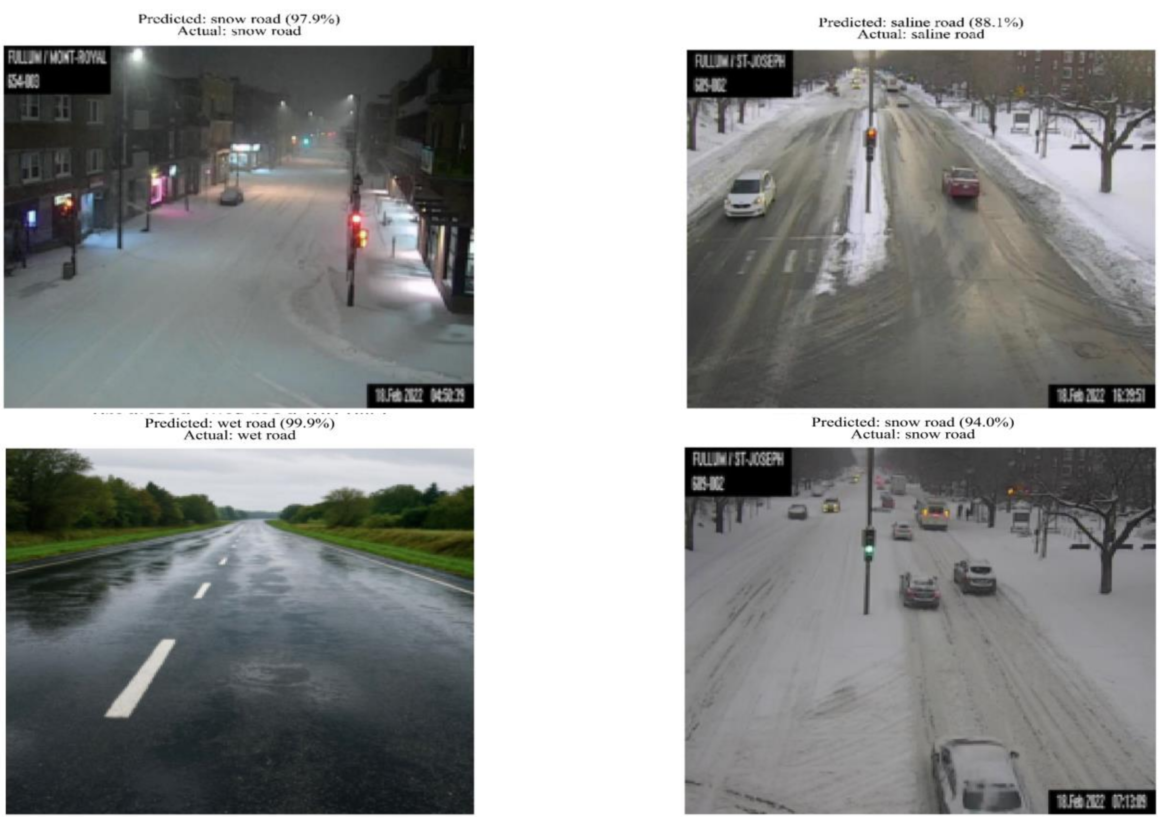

Fig. 8 Road surface classification using ResNet101. The model correctly predicted the image as a saline road, sown road, and wet road with 88.1%, 97.9%, and 99.9% confidence, respectively

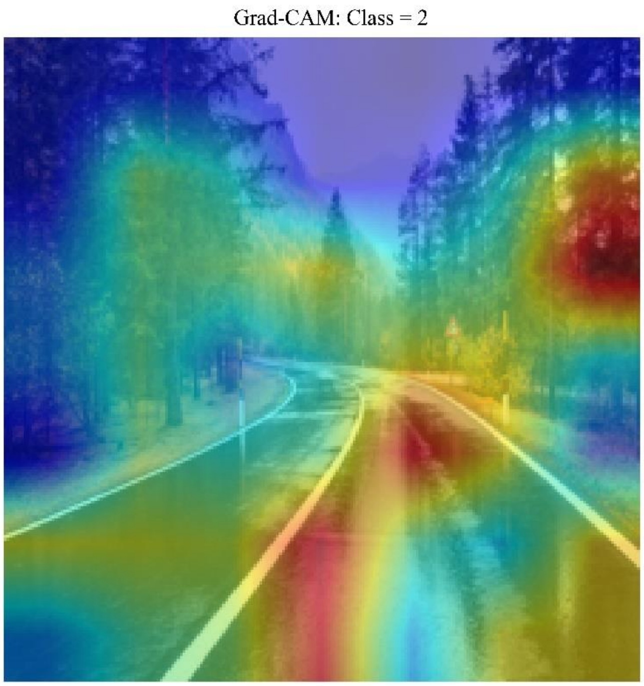

Fig. 9 Grad-CAM visualization highlighting the areas of focus in the road surface during classification

Sensor node captures and computes the trigger value on 6 different parameters like temperature, humidity, dew point, precipitation, wind speed, and wind direction. These inputs were fed into a rule-based logic engine to assess the risk of black ice. In parallel, a camera module performed real-time road condition classification into four categories: dry, wet, saline, and snow. Black ice warnings were issued based on a combination of logic thresholds and visual analysis, with the system's performance demonstrated through prediction samples, classification metrics, and attention heatmaps to provide insight into the model's decision-making process. The model exhibited high classification confidence for snow and saline roads, with confidence scores ranging from 62.5% to 97.9%, as demonstrated in the figures. These results indicate strong model generalisation across varied conditions, including low light, snow glare, and variable textures in road surfaces. This was further confirmed through visual attention maps generated using Gradient Weighted Class Activation Mapping Grad-CAM [32], where the model consistently focused on relevant surface features such as reflective wet patches and snow accumulation lines, as shown in Figure 9.

The study result shows the ResNet101-based road classification model was trained over 10 epochs using the Adam optimizer [33] with a learning rate of 0.001, targeting a cross-entropy loss. A transfer learning approach was adopted by freezing the convolutional layers and improving specifically the fully integrated layers. This helped the model adapt efficiently to the dataset while reducing the risk of overfitting. As shown in Figure 10, the training accuracy reflected a systematic enhancement from 71.0% to 95.6%, with the validation accuracy achieving its highest point at 95.2% in epoch 9 and wrapping up at 92.8% in epoch 10.

The small gap between training and validation accuracy (less than 2.5% on average) indicates strong generalization and effective data augmentation. The accuracy curve begins to flatten after epoch 6, suggesting that the model had successfully learned the key patterns [34]. This stable learning behaviour is especially important when dealing with varying road and weather conditions. The training results validate the model's reliability and the choices made in both architecture and optimization strategy.

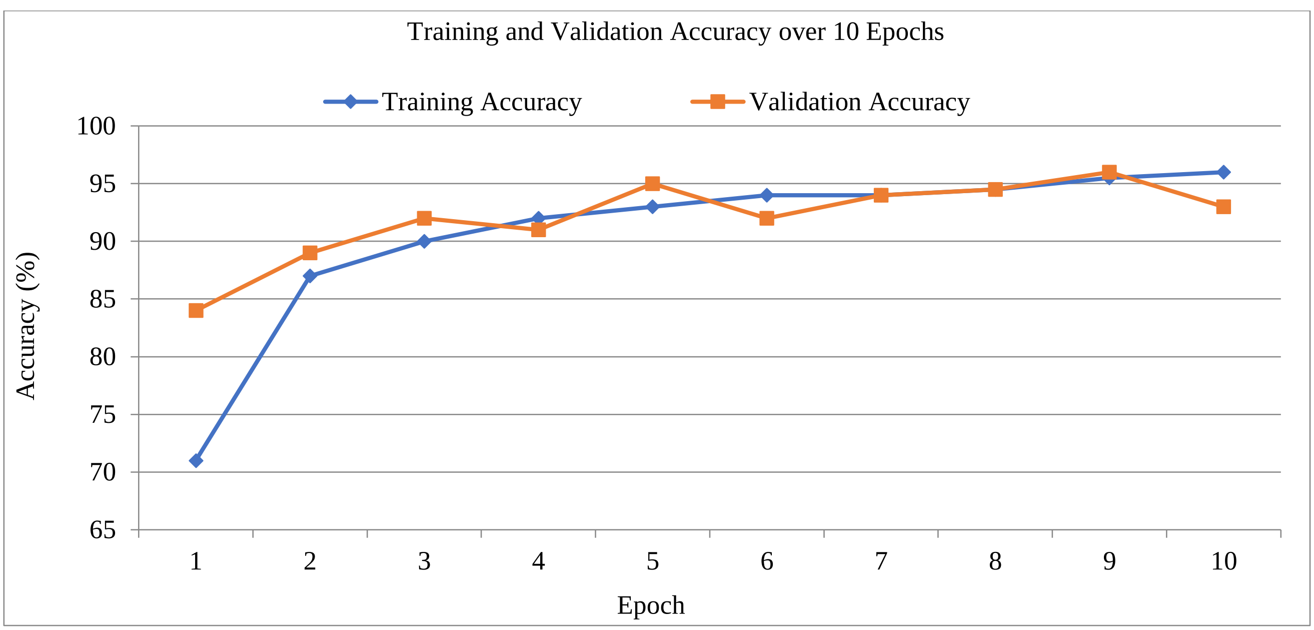

Fig. 10 Training and validation accuracy trends showing stable convergence over 10 epochs

To evaluate the classification performance and reliability of the trained model, a per-class confusion matrix [35] was computed, as shown in Figure 14. The matrix captures the distribution of true labels versus predicted labels across all four road condition categories: dry, wet, saline, and snow. The diagonal entries represent correctly classified instances, while off-diagonal elements highlight misclassifications.

The model exhibits excellent classification accuracy for dry roads (103/104 correctly identified) and snow roads (105/106), shown in Figure 11, reflecting strong generalization for visually distinct surface textures and color distributions. Wet road conditions, while correctly predicted in 73 instances, experienced minor confusion with dry (1), saline (1), and snow (1) categories, likely due to shared reflective or low texture surface features under certain lighting conditions.

The saline road class demonstrated the highest degree of misclassification, with 7 images misidentified as wet roads and 1 each as snow and dry. This can be attributed to visual similarities between partially cleared saline-treated roads and wet/slushy surfaces. Nonetheless, 90 out of 99 saline road samples were accurately classified, yielding a class-specific accuracy of 90.9%.

These observations are quantitatively aligned with precision-recall analysis, where the macro average precision remained above 92%, and recall for the snow road class peaked at 99%. The model's confusion matrix thus validates the robustness of its predictions and identifies categories that require improved differentiation, potentially through enhanced data augmentation or domain-specific feature extraction.

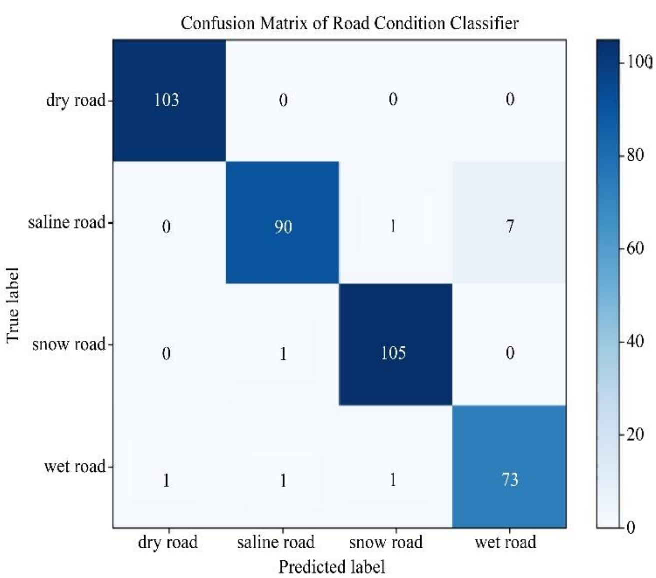

Fig. 11 Confusion matrix of the road condition classifier showing class-wise prediction performance

Table 3. Precision, recall, and F1-score for each road surface class predicted by the model [36]

Condition	Precision	Recall	f1-Score	Support
Dry Road	0.981	0.990	0.986	104
Saline Road	0.978	0.909	0.942	99
Snow Road	0.981	0.991	0.986	106
Wet Road	0.901	0.961	0.930	76
Accuracy	0.964	0.964	0.964	0.964
Macro Avg	0.960	0.963	0.961	385
Weighted Avg	0.965	0.964	0.964	385

The classification report summarises the performance of the ResNet101 model across four road surface classes in Table 3. Precision and recall are highest for snow and dry road categories, indicating consistent predictions. The model achieves an overall accuracy of 96.36%, with macro and weighted averages above 96%, demonstrating strong generalization.

Fig. 12 Dry road scenario with sensor data

Fig. 13 Wet road scenario with sensor data

The road condition is classified as dry by the ResNet101 model. Despite sensor inputs indicating high humidity (95.0%) and a low temperature (-1.0°C), the precipitation level is 0 mm, and the visual condition confirms a dry surface. Thus, the system logically concludes that no black ice is present as shown in Figure 12 and in Figure 13 the road surface is visually detected as wet, and sensor readings show a temperature of -1.0°C, dew point at -1.7°C, high humidity (95.0%), and precipitation of 1.0 mm. These parameters together satisfy the triggering logic conditions, leading the system to accurately predict black ice detected. Evaluation of individual sensor-based conditions contributing to black ice detection across 8 test cases. Each row indicates a different condition, while each column relates to an individual test case. Red markers indicate that the condition was met and black ice was predicted, while green shows no black ice prediction despite the condition being met. 'X' markers represent conditions that were not met. This analysis illustrates how multiple simultaneous factors are required to trigger a black ice warning. AER-Net showed moderate performance; the final model, ResNet101, pre-trained and fine-tuned on road surface condition data, achieved the highest accuracy (95.6%) and F1-score (~94%). The use of residual connections, deeper convolutional layers, and transfer learning significantly improved generalization. Unlike the AER-Net, which requires BiLSTM and attention mechanisms to boost temporal understanding, ResNet101 efficiently captures spatial features from static road images, making it more suitable for embedded deployment in real-time systems.

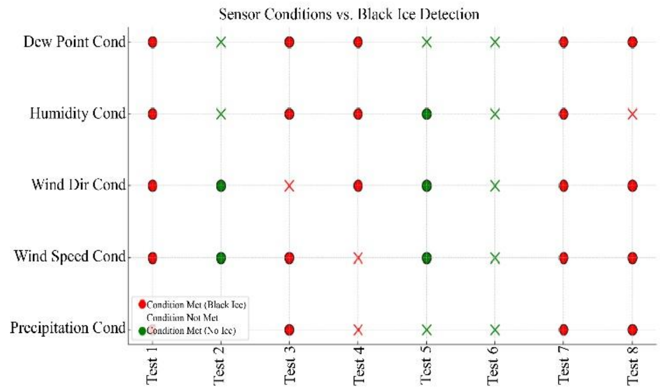

Fig. 14 Sensor conditions were met and how they relate to black ice detection for each test case

Table 4. Sensor data with visual classification, triggering alerts based on set thresholds and confirmed image analysis

Model Variant	Residual Connections	BiLSTM	Attention	Accuracy (%)	F1-Score (%) (approx)
Baseline CNN	✕	✕	✕	80.39%	~80%
CNN + Residuals	✓	✕	✕	78.86%	~79%
CNN + Residuals + BiLSTM + Attention (AER-Net)	✓	✓	✓	87.7%	~88%
ResNet101 (Final Model)	✓	✕	✕	95.6%	~96%

6. Conclusion and Future Scope

In this research, a comprehensive and intelligent approach was developed for black ice detection by integrating environmental sensing with deep learning-based vision analysis. By using real time data from sensors measuring temperature, humidity, dew point, precipitation, wind direction, and wind speed, and all the parameter when meet with the suitable conditions it will trigger and combined with a Machine Learning based classifier trained on road images categorized as dry, wet, saline, and snow, the system achieved a high validation accuracy of 95.6%. The logic engine used these sensor values to determine potential black ice conditions, while the vision model provided visual confirmation of road surface types. This hybrid architecture not only ensured accurate detection but also reduced false positives by verifying the prediction through both data modalities. Grad-CAM visualizations further confirmed that the model's predictions were based on meaningful image features.

Looking forward, this system can be expanded by integrating real-time cloud connectivity for remote monitoring, deploying lightweight versions on edge AI devices for faster roadside or vehicular response, and extending training with more diverse seasonal data from regions such as Uttarakhand, Himachal Pradesh, and Kashmir. Additionally, future enhancements could include estimating the severity of black ice and interfacing with vehicular safety systems to issue timely alerts. Overall, the study demonstrates a promising step toward a reliable, scalable, and intelligent solution for proactive road safety during adverse winter conditions.

6.1. Limitations and Future Research Directions

This system looks like it could really help make roads safer, especially in cold or hilly areas. But still, there are some points that need to be considered. For one, the training data came from just a few places. That means it might not work as well in other regions unless it gets updated or retrained. Also, LoRa tech can send signals far and doesn't use much power, but it might not work great in areas full of trees, buildings, or mountains, since that can mess with the signal.

This system only tells you if black ice is there or not; it doesn't say how bad it is. Down the line, the system could be improved by adding devices that can handle things faster on the spot, like Jetson Nano or Coral TPU. Getting more data from all kinds of weather, road types, and lighting would help make it more reliable. A simple mobile app or web dashboard could also make it easier to check the info. Eventually, it could even link up with cars to send alerts or work with safety features like anti-lock brakes to help drivers avoid crashes.

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