Detection of Black Ice in Autonomous Vehicles Using Inertial Measurement Based Binary Classification Neural Network

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Abstract - **Black ice poses significant challenges to driving, specifically autonomous driving, due to its difficulty to detect and its impacts on the vehicle safety. Present methods for detecting black ice, although accurate, are still vulnerable to external environmental influences and cannot function in certain environments. Therefore, the research looks into novel methods of all environment black ice detection, using inertial measurement data collected with a scale model of vehicles to train neural networks for binary classification of road conditions. The resulting method from two separate neural network structures are 98.8% and 99.5% accurate respectively, and deployment of the neural network onto Tensor Processing Units (TPU) is proved to be feasible with the average inference time being 0.75 milliseconds and the standard deviation being 0.13 milliseconds. A Two Proportions Z-Test also proves the method's improvement in accuracy to be statistically significant.**

Index Terms—**Autonomous Vehicle, Black Ice, Inertial Measurement, Neural Network, Machine Learning, Remote Sensing**

INTRODUCTION

The autonomous vehicle industry is a rapidly growing sector in the current society. With examples such as Tesla's Full Self-Driving mode to Waymo, formerly known as Google Self-Driving Car Project, multiple companies have demonstrated interest in the newly researched technology and highlighted the potential of autonomous vehicles in improving road safeties and reducing traffic congestions. As of 2023, there are an estimated 30 million vehicles with some extent of autonomous capabilities in the global market. Moreover, according to current projections, by 2025, over 60 percent of all new vehicles will have level 2 autonomy, meaning that the system can drive autonomously under the supervision of a human driver.

However, there are also doubts over the safety of autonomous vehicles. Since 2019, Tesla's autopilot cars have been involved in 736 crashes, with 17 leading to fatalities. Meanwhile, in a research conducted in 2022, more than 44 percent of American adults believe that widespread use of autonomous vehicles would be negative for society, with only 26 percent supporting autonomous vehicles. In another report that recounted multiple polls of public opinion on autonomous vehicles, the majority of the respondents were at the very least skeptical of the safety standards of autonomous vehicles.

One of the primary challenges for autonomous driving safety is environmental conditions, with one prominent example being black ice, a layer of transparent ice that forms on roads under low temperatures. Autonomous vehicles are not designed to handle complex terrain, and often suffer from the same issues that affect human drivers. Therefore, in cases such as icy or snowy road conditions, the risk of accidents is significantly increased for both human drivers and autonomous vehicles. According to the Department of Transportation, over 116,800 people are injured and over 1300 are killed in accidents on snowy or icy roads. Meanwhile, over 70 percent of the nation's roads are located in regions that receive more than 13 centimeters of snow annually, and over 70 percent of Americans live in snowy regions [1].

Therefore, the need for a system that can improve the safety of driving in icy and snowy road conditions is evident. As a result, the paper focuses on creating an all environment black ice detection system for autonomous vehicles that remains accurate under severe environmental influences.

Fig. 1: Image of Black Ice [2]

I. LITERATURE REVIEW

A. *Overview*

The preexisting detection methods can largely be divided into contact based methods and remote sensing based methods, with the former requiring physical contact between the sensor and the ice, and the latter having the ability to detect ice from a distance using a variety of remote sensors such as cameras and millimeter wave (mmWave) sensors. The section will examine some of the previous research in these fields, and analyze potential problems that can be addressed.

B. *Contact Based Ice Detection*

Liu et al. [3] developed a method that uses the change in conductivity between normal roads and icy roads to detect black ice, which uses normal temperature and conductivity sensors, reducing the cost of implementation for the detection system.

Trevino et al. [4] developed a method that uses the moisture and temperature sensors to detect black ice, with the sensors being embedded in the roads.

C. *Remote Sensing Based Ice Detection*

Lee et al. [5] trained a neural network based on images of different road conditions on the internet, and eventually achieved a 98 percent accuracy in black ice detection.

Kim et al. [6] used a mmWave sensor and combined it with neural networks for black ice detection, and achieved a 98.2 percent accuracy in indoor experiments as well as high accuracies under low light and outdoor conditions.

Abdalla et al. [7] used Microsoft Kinect, which is a motion sensor equipped with RGB camera and infrared depth sensors, to detect black ice using geometry. They eventually achieved an error rate of only 2 centimeters when detecting distance to the black ice as well as when assessing the thickness of the ice.

D. *Analysis and Conclusion*

Although both types of terrain classification are proven to be accurate, each of them has certain flaws that prevent them from being effective under all conditions.

For contact based sensors, these methods are mainly proposed to be used for road controls rather than direct input to the vehicle control system. Moreover, the large quantities of these sensors that will be required for all major highways and roads will not only increase the cost of implementation, but also make sensor integration with autonomous vehicles difficult to implement.

Meanwhile, for the remote sensing based approaches, they are all susceptible to environmental factors and their damages to the algorithms. For example, in the camera based approaches, the detection accuracy is easily affected by foggy weather or lighting conditions, which prevents the camera from obtaining accurate photos for the algorithms to analyze. In other approaches such as the mmWave based methods, the reflectivity of the surrounding environment will also affect the reflection of the waves, which subsequently impacts the accuracy of the analysis model. As a result, there is currently no effective black ice detection method that works and maintains high accuracy under all environmental conditions.

II. RESEARCH GOAL & DESIGN

As a result of the above mentioned problem, the research aims to develop a novel all environment black ice detection method that works under all condition and can be deployed onto an autonomous car to yield accurate detection results. In the end, the new detection method is designed to be based on accelerometer and gyroscope readings, which in theory are always accurate and thus would work under all environments. The sensor values will then be processed using a binary neural network, and used to generate classification results of normal road conditions or icy road conditions. Therefore, the project requires the building of a scale model of vehicle to collect data, and the designing of neural networks for accurate classifications.

III. IMPLEMENTATION & METHOD

The implementation and method of the research can largely be divided into the model design phase, the neural network design phase, and the data collection phase, with each part covering different aspects of the project. The section will provide an overview of each part, and the engineering process that was implemented.

A. *Model Design*

The model design is based on Ackerman-Steering structure, in which the front wheels are used for turning and the black wheels remain fixed in angles. The vehicle is assembled using one SG90 servo as the steering servo, and two TT motors as the back wheel motors. The servo is controlled by setting its turning angles, with each side having 50 degrees of freedom. The back motors are controlled with pulses, with the minimal pulse set to 100 and the maximum pulse set to 200. The servo and motors are controlled using a Raspberry Pi 4 and a PWR.A53.A motor driver board. The Raspberry Pi, the servo, and the motors are all powered by an onboard lithium battery. An LSM9DS1 IMU is attached to the car on a breadboard, and is connected to the Raspberry Pi through SPI connection using jumper wires. The vehicle is also waterproofed using plastics wraps to protect the electronics from possible damage.

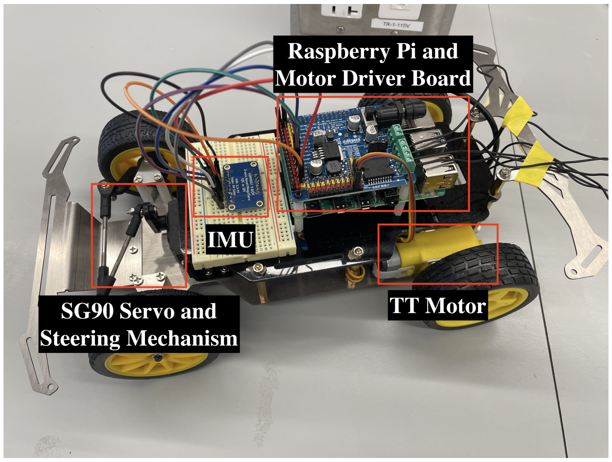


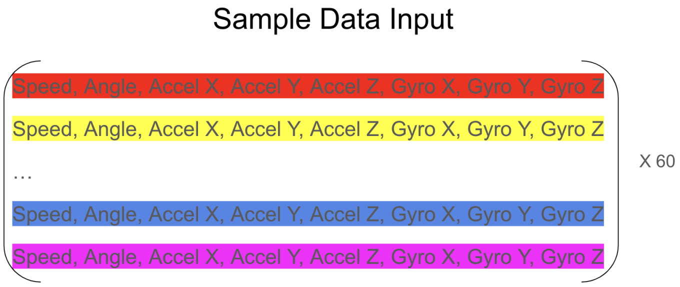
Fig. 2: Diagram of the Model Vehicle

Meanwhile, the vehicle is setup to be controlled using a GameSir controller through a wireless dongle, seeing that Bluetooth connection often seems unreliable for the Raspberry Pi. The code uses the Pygame library to monitor controller inputs, and sends commands to the vehicle at a frequency of 60 Hz. The left joystick of the controller is mapped to control the speed of the vehicle, while the right joystick is mapped to control the turning angle of the vehicle. Both controller inputs are adjusted to the maximum and minimum input values for the servo and motors, allowing for proportional control of the vehicle. Meanwhile, the left trigger is mapped to be the dead man's switch, which stops the vehicle when the driver releases the trigger. It also acts as a recording button, which records the speed, the angle, and the IMU values into a list while being pressed. The right trigger serves as the labeling button, allowing the driver to label the data as icy road data by pressing the button. At last, the pressing the X button saves the data into a CSV file, and pressing the Y button stops the driving program.

Fig. 3: Diagram of the Controller Layout

B. Neural Network Design

For the neural network models, they are expected to take in 60 rows of data, with each row containing the speed of the vehicle, the angle of the vehicle, the 3-axis accelerometer reading, and the 3-axis gyroscope reading of the vehicle. In theory, by using a continuous segment of data, which in the research represents 1 second of driving data, provides the neural network context of the data compared to an instantaneous input, the neural network will be able to make more accurate predictions. Meanwhile, the neural network will output binary classification results using the data, with 0 representing normal road conditions and 1 representing icy road conditions.


Sample Data Input

Speed, Angle, Accel X, Accel Y, Accel Z, Gyro X, Gyro Y, Gyro Z
Speed, Angle, Accel X, Accel Y, Accel Z, Gyro X, Gyro Y, Gyro Z
…
Speed, Angle, Accel X, Accel Y, Accel Z, Gyro X, Gyro Y, Gyro Z
Speed, Angle, Accel X, Accel Y, Accel Z, Gyro X, Gyro Y, Gyro Z

Fig. 4: Structure of Data Input

The research includes two neural network designs, with one being a traditional Convolutional Neural Network (CNN), and the other one being a Recurrent Neural Network (RNN). By using two separate architectures, the research hopes to examine the accuracy that each model yields as well as the computational power required by each model in order to find the optimized model design for black ice detection.

The Convolutional Neural Network is made up of 3 ReLU layers, with each one containing 768 nodes, and a Softmax layer. Notably, the data is also preprocessed through a flattening function to be passed into the neural network as an 1-dimensional array.

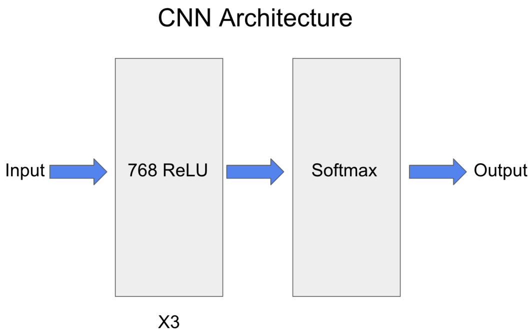


Fig. 5: Structure of the CNN Model

Meanwhile, the Recurrent Neural Network is made up of 1 Long Short-Tern Memory (LSTM) Layer with 256 nodes, 1 ReLU layer with 128 nodes, and a Softmax layer. Since the LSTM layer is more computationally intensive compared to ReLU layers, the number of nodes and layers are both reduced compared to the CNN model.

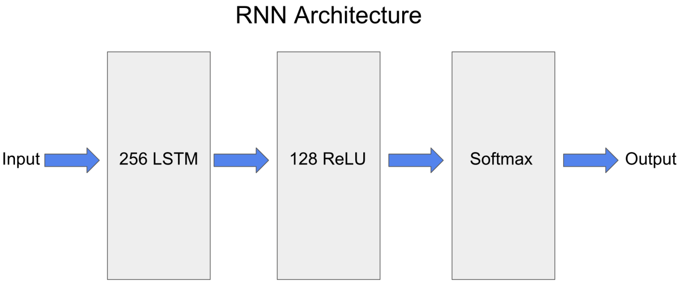


Fig. 6: Structure of the RNN Model

C. Data Collection

The data collection is conducted using two separate terrains, with the normal road condition being simulated with indoor pavement, and the icy road condition being simulated with the ice rink. While it is possible to include driving conditions such the transition from normal driving conditions to icy conditions or partially icy terrains, the research is limited to completely normal road conditions and completely icy road conditions in order to limit its scope to binary classification.

Fig. 7: Simulated Normal and Icy Road Conditions

The data collection is split into three phases. The first phase serves as a testing phase, where small amounts of data is collected to prove the validity of the concept and checking to see if there is correlation between the IMU data and road conditions. The second phase serves as a fine-tuning phase, where more data is collected to adjust the parameters of the models such as learning rate and batch size for optimizing their accuracy. At last, the final phase of data collection is the final training phase, where as much data as possible is collected to generate the finalized classification model. In the research, the data size for each phase is 22,000 datapoints, 48,000 datapoints, and 110,000 datapoints respectively. In the end, the data is split into a training dataset, a validation dataset, and a testing dataset by a 70:15:15 proportion, which aims to avoid overfitting while at the same time giving the model enough data to simulate all driving conditions.

IV. RESULTS & DATA ANALYSIS

After training on the 110,000 large dataset, both models yielded high accuracies for both normal road conditions and icy road conditions classification. For the CNN architecture, the finalized model is 99.5 percent accurate, with its error split displayed in Figure 9. Simiarly, the RNN architecture yielded a 98.8 percent accuracy, with its error split shown in Figure 10.

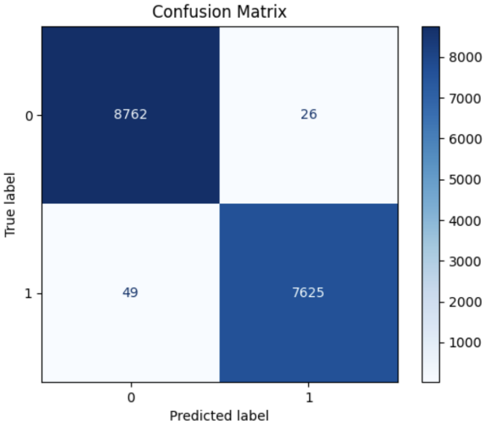


Fig. 8: Finalized CNN Model Confusion Matrix

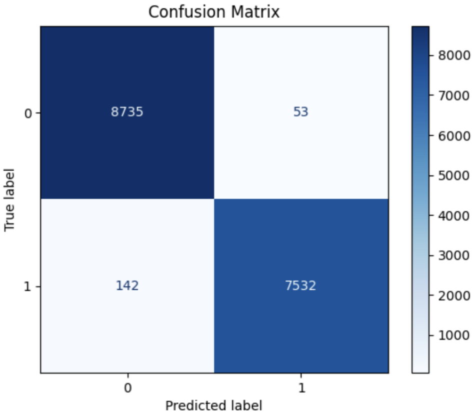


Fig. 9: Finalized RNN Model Confusion Matrix

A Two Proportions Z Test is then performed on the finalized CNN model and the aforementioned accuracy of the mmWave based detection method with an α value of 0.05. The P value for icy terrain classification is calculated to be 0.0228, while the P value for normal terrain classification is calculated to be less than 0.0001. Since both values are less than α, the null hypothesis can be rejected, and the method's improved accuracy over the mmWave sensor approach is proven to be statistically significant.

At last, the CNN model is also quantized and deployed onto a Google Coral Edge TPU, which is specialized for accelerating the inference of neural networks and runs at 4 trillion operations per second. The Edge TPU is then connected to the Raspberry Pi, which directly inputs the collected data into the model deployed on the Edge TPU for real time classification of the terrain. The average inference time is 0.75 milliseconds, with a standard deviation of 0.13 milliseconds. As seen in Figure 10, the distribution is skewed to the right, and the majority of classifications are performed with 1 millisecond.

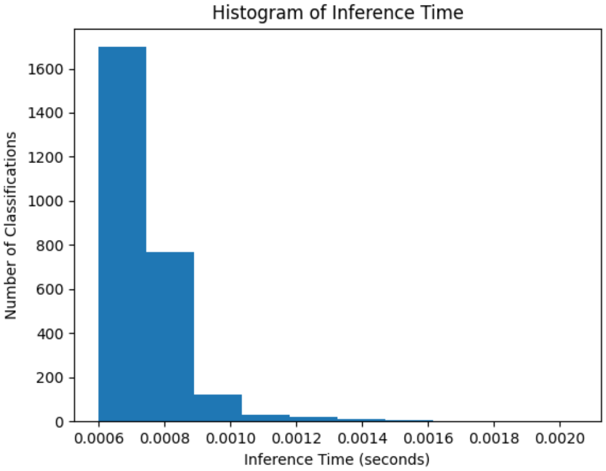


Fig. 10: Histogram of the Model's Inference Time

CONCLUSION

In conclusion, the inertial measurement based black ice detection method developed in the research is not only able to function under all types of environmental influences due to the nature of inertial measurement data, but is also more accurate compared to previous black ice detection methods.

However, the new detection method can be further improved by collecting more data and further improving the accuracy of the models, as well as increasing the types of classification to enable detection of wet roads, snowy roads, and partially icy roads. At last, it is also possible to develop a Multi-Axis Inertial Grouping Operation (MAIGO) that classifies all terrains using their inertial properties, which will make the detection method more useful by expanding its range of applications.

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REFERENCES

[1] Federal Highway Administration, “Snow and Ice - FHWA Road Weather Management,” Dot.gov, 2019.
[2] Wikimedia Commons, ”2023-01-19 Plötzliches Glatteis und gefrorene Pfützen in Tauberbischofsheim”.
[3] T. Liu, Q. Pan, J. Sanchez, S. Sun, N. Wang and H. Yu, ”Prototype Decision Support System for Black Ice Detection and Road Closure Control,” in IEEE Intelligent Transportation Systems Magazine, vol. 9, no. 2, pp. 91-102, Summer 2017, doi: 10.1109/MITS.2017.2666587.
[4] M. Trevino, T. Dossey, Y. Yildirim, M. Barrett, C. Shaw, A. Ongel, E. Kohler, Q. Lu, H. Wang, and G. Flintsch, “Black ice detection in open-graded friction courses,” in Proc. TRB Annu. Meeting, 2007.
[5] H. Lee, K. Hwang, M. Kang and J. Song, ”Black ice detection using CNN for the Prevention of Accidents in Automated Vehicle,” 2020 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2020, pp. 1189-1192, doi: 10.1109/CSCI51800.2020.00222.
[6] J. Kim, E. Kim, and D. Kim, “A Black Ice Detection Method Based on 1-Dimensional CNN Using mmWave Sensor Backscattering,” Remote Sensing, vol. 14, no. 20, p. 5252, Oct. 2022, doi: 10.3390/rs14205252.
[7] Y. E. Abdalla, M. T. Iqbal and M. Shehata, ”Black Ice detection system using Kinect,” 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, 2017, pp. 1-4, doi: 10.1109/CCECE.2017.7946722.