IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Acoustic Fog Detection Using Ultrasonic Attenuation And Machine Learning For Real-Time Visibility Prediction

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Abstract

Fog and mist lower visibility and raise the risk of road crashes. India recorded more than 34,000 such crashes in 2022. AVPM provides a low-cost and light-independent method to estimate visibility. The system measures how fog weakens an ultrasonic signal. It records amplitude, humidity, and temperature. It feeds this data into machine learning models. These models predict visibility in meters and assign a hazard level through a Fog Hazard Index. The study covers the sensor design, the data collection plan, the model tests, and the index rules. Past research shows that sound loss in fog can be measured. AVPM builds on this finding and offers a path for field use in regions that face dense winter fog.

Keywords : Ultrasonic Attenuation, Fog Detection, Visibility Estimation, Machine Learning, Road Safety, Acoustic Sensing, Fog Hazard Index

Introduction

Fog is a layer of tiny liquid water droplets in the lower atmosphere. It sharply reduces road visibility and leads to chain crashes and deaths. In 1990, one dense fog event on I-75 in the United States caused a 99-vehicle pile-up. That crash killed 12 people and injured 42. In India, fog on roads remains a major problem. In 2022, 34,262 road accidents were linked to foggy or misty conditions.

Most present fog detection and visibility tools use optical methods. These include camera systems, infrared sensors, and LIDAR units. Many such systems fail in dense fog or low light. Camera tools depend on street lighting or headlamps. Infrared and LIDAR units need high hardware cost and regular upkeep. Rural highways and low-resource regions rarely support such systems.

Acoustic sensing offers a different path. Ultrasonic sound travels through air without any need for ambient light. Fog adds water droplets to the air and these droplets absorb and scatter sound. The sound intensity then falls with distance. This loss of intensity can reflect fog density and visibility range. If this relation stays stable and measurable, it can support a real-time and low-cost visibility meter.

This paper presents the Acoustic Visibility Prediction Model, or AVPM. The work has three main aims. The first is to measure ultrasonic attenuation under controlled fog conditions. The second is to build a dataset that joins acoustic readings with humidity, temperature, and ground-truth visibility. The third is to train machine learning models that predict real-world visibility from this data. The study also defines a Fog Hazard Index that converts predicted visibility and related factors into clear risk levels for drivers and highway control rooms.

Background

Fog consists of suspended microscopic water droplets (typically 1–20 μm) that scatter both light and sound. This scattering leads to reduced visibility on roads and also causes attenuation of ultrasonic waves. According to ITU-R P.840-7, sound attenuation in fog increases nonlinearly as droplet concentration increases.

Traditional visibility detection systems use optical methods such as LIDAR, IR sensors, or transmissometers. However, these systems perform poorly in low light or night-time conditions and are expensive to deploy on highways. Recent studies (EGUsphere 2025; MDPI Atmosphere 2022) show that signal attenuation in communications links can serve as a reliable proxy for fog density, and machine learning can model the complex relationships between environmental variables and visibility.

However, there are no low-cost fog detection solutions using ultrasonic attenuation combined with machine learning. Since ultrasonic sensors are inexpensive, robust against lighting variations, and simple to deploy, they present a promising new direction for mass-scale fog visibility monitoring. This project explores this potential by experimentally measuring ultrasonic attenuation through controlled fog and training ML models to estimate visibility.

Literature Review / Scientific Background

Fog, Visibility, and Road Safety

Fog and mist cut road visibility and raise crash risk. Drivers see less of the road, and reaction distance shrinks. Multi-vehicle collisions and pile-ups then become more likely.
In India, official data report tens of thousands of fog-related crashes each year. Many of these crashes occur on high-speed corridors in winter mornings. Dense fog on expressways often leads to long chains of damaged vehicles and long closures.

Advanced fog-detection tools exist, such as LIDAR and infrared units. Camera-based systems also track visibility using road images. These tools need high hardware cost, trained staff, and steady power. They often depend on street lighting or headlamps. Many rural or low-resource regions do not support such systems. As a result, highways with heavy fog still run without active visibility monitoring.

Acoustic Wave Propagation in Fog and Droplet Mixtures

Sound waves in air lose energy as they pass through fog. The air contains tiny water droplets. These droplets create viscous loss, thermal loss, and scattering of sound energy. Early lab studies tested sound absorption in artificial fog and cloud chambers. Researchers used fixed droplet sizes and controlled humidity. They measured how sound level fell with distance.

Later work extended these tests to ultrasonic ranges. Studies mapped ultrasonic attenuation against droplet radius, droplet number, and sound frequency. The attenuation coefficient showed strong links with droplet radius and ultrasonic frequency. Higher fog density and certain droplet sizes produced higher loss.

These results support the use of ultrasonic sensors for fog sensing. Sound waves at ultrasonic frequencies pass through dark or low-light scenes without any need for light. Measured loss in amplitude can track fog density and, by extension, visibility range. This physical link forms the base for the AVPM design.

Gaps and Novelty

Past work on acoustic attenuation in fog sits mainly in physics and acoustics. It does not extend to road visibility measurement. Existing road visibility tools still rely on cameras, infrared sensors, or LIDAR. No published system combines ultrasonic attenuation, machine learning, and environmental sensing to predict road visibility in real time.

AVPM fills this gap. It links atmospheric physics, acoustics, embedded hardware, and data science in one design. No current visibility tool joins ultrasonic physics, environmental sensing, and machine learning into a single fog hazard meter. AVPM is the first system to do this for road safety.

Calibration Protocol

Each AVPM unit runs a calibration step in clear air. The system records a baseline signal amplitude under these conditions. Later, it expresses every attenuation value as a change from this baseline.

Methodology and Experimental Design

Overview

The study follows six main steps.

- Build a test chamber with controlled fog generation.
- Install an ultrasonic transmitter, receiver, and environmental sensors.
- Measure sound attenuation and optical visibility across a wide range of fog densities.
- Record a large dataset of acoustic readings, sensor values, and ground-truth visibility.
- Create features and train machine learning models for regression and classification tasks.
- Define a Fog Hazard Index based on model outputs and key environmental factors.

Experimental Setup

Hardware components

The AVPM test rig uses a simple, low-cost hardware stack. The main elements are:

- A 40 kHz ultrasonic transmitter and receiver, such as an HC-SR04 pair or separate TX/RX units.
- A microcontroller board, such as Arduino or ESP32, to send pulses and record received amplitude.
- A fog source, such as an ultrasonic humidifier or mist maker.
- A closed transparent chamber made from acrylic or plastic to hold the fog.
- A visibility meter, built in one of two ways:
    - a laser pointer aligned with a photodiode or light sensor, or
    - a camera that views a high-contrast target with a black and white pattern.

- A temperature and humidity sensor, for example a DHT22 module.
- Rigid mounts and fixtures that keep all devices at fixed positions.

Layout and procedure

The ultrasonic path follows a straight line. The transmitter and receiver face each other across a fog path of 50 to 100 cm. The chamber holds the fog between them.

The visibility meter sits on a second optical path. The path crosses the fog volume at a right angle to the sound path. In the laser version, the laser points at the light sensor across the chamber. In the camera version, the camera views the target through the fog.

The fog source raises droplet density in steps. The operator sets a fog level and waits for stable readings. The system then records ultrasonic amplitude, temperature, humidity, and visibility.

Each fog level uses repeated trials to reduce noise. A typical set uses 5 to 10 readings per level. The experiment repeats these steps under different humidity and temperature states. This process builds a dataset that spans clear air, light fog, medium fog, and dense fog.

Variable Type	Variables
Independent	Fog generation duration; chamber humidity (%); ambient temperature (°C)
Dependent	Ultrasonic received amplitude; visibility metric (light intensity / visibility category)
Controlled	Distance, chamber geometry, background noise and light conditions

Data Collection Strategy

The target dataset holds about 1,000 records. These records span 10 to 15 fog levels. Each level appears under slightly different humidity and temperature states.

Each data point stores the following fields:

- Humidity (%)
- Temperature (°C)
- Fog duration (time since fog start)
- Raw received ultrasonic amplitude
- Calculated attenuation in dB relative to clear air
- Visibility metric from the optical path
- Trial number
- Timestamp

This plan gives a dense grid over fog levels and environmental conditions. It supports both regression and classification tasks.

Rationale for Choosing Machine Learning

Fog attenuation is nonlinear because sound is scattered and absorbed by droplets in complex ways that depend on droplet size, humidity, temperature, and fog formation time. Linear threshold-based methods fail to capture these interactions. Machine learning allows multiple features (attenuation, humidity, temperature, SNR, fog duration) to be combined, enabling accurate prediction of visibility levels. This is especially useful in safety-critical contexts where under- or over-estimating fog severity can cause serious accidents.

Feature Engineering

The raw logs feed a feature set that joins acoustic, environmental, and optical

data. Acoustic features include:

- Raw amplitude of the received ultrasonic signal
- Attenuation in dB, relative to the clear-air baseline
- Signal-to-noise ratio of the received pulses
- Variation in amplitude across a short pulse

window Environmental features include:

- Humidity in percent
- Temperature in degrees Celsius
- Fog duration at the time of reading

An optional optical feature records light intensity or turbidity on the visibility path.

A typical feature vector takes the

form [
X = [\text{Humidity}, \text{Temperature}, \text{FogDuration}, \text{Attenuation_dB}, \text{SNR}]
]

The targets come in two forms.
The regression target is the estimated visibility distance in meters. The classification target is a discrete class label. One example set is:

- Clear: visibility above 200 m
- Moderate: visibility from 100 m to 200 m
- Low: visibility from 50 m to 100 m
- Very low: visibility below 50 m

Machine Learning Pipeline

The pipeline follows a standard supervised learning

workflow. The dataset splits into three parts:

- 70% for training
- 15% for validation
- 15% for final testing

For regression, the study trains the following models:

- Linear Regression as a baseline
- Random Forest Regressor

- Gradient Boosting model, such as XGBoost
- Support Vector Regressor
- A small Multilayer Perceptron

For visibility classes, the study trains these models:

- Logistic Regression
- Random Forest Classifier
- Gradient Boosted Classifier
- Multilayer Perceptron

Regression performance uses three metrics: Mean Absolute Error, Root Mean Squared Error, and (R^2). Classification performance uses accuracy, precision, recall, F1-score, and the confusion matrix.

Fog Hazard Index (FHI)

The Fog Hazard Index compresses multiple risk factors into one scalar score. The score lies between 0 and 1. Higher values mark higher hazard.

Let

- (V) be the predicted visibility distance in meters, from the regression model.
- (H) be the relative humidity in percent.
- (A) be the ultrasonic attenuation in dB, relative to the clear-air baseline.
- (A_{\text{max}}) be the maximum attenuation value observed in the dataset.

The FHI is defined as

[
\mathrm{FHI} = \alpha \cdot \frac{1}{V} + \beta \cdot \frac{H}{100} + \gamma \cdot \frac{A}{A_{\text{max}}}
]

The three terms reflect different physical drivers of fog risk. The term (1/V) increases when visibility falls.
The term (H/100) grows with ambient humidity.
The term (A/A_{\text{max}}) tracks relative acoustic loss inside the fog.

The weights (\alpha), (\beta), and (\gamma) set the relative importance of each factor. The study tunes these weights through cross-validation and expert judgment.
A typical choice is (\alpha = 0.5), (\beta = 0.3), and (\gamma = 0.2).

FHI categories

The continuous FHI score maps to four hazard bands:

- FHI in ([0.00, 0.25]): **Safe**
- FHI in ((0.25, 0.50]): **Caution**
- FHI in ((0.50, 0.75]): **Dangerous**
- FHI in ((0.75, 1.00]): **Extreme Hazard**

These bands give a direct link from sensor readings to field actions.
The AVPM unit can drive in-vehicle alerts, roadside variable message signs, or automatic speed-control protocols through the FHI output.

Expected Results

Past acoustic studies report clear extra sound loss in fog and cloud at ultrasonic frequencies. The loss appears in dB and is easy to measure with stable hardware.

Given this base, a clean dataset should support strong regression fits. For AVPM, we expect a visibility RMSE on the order of 10 to 25 meters. The exact value will depend on fog thickness, chamber size, and how uniform the fog field is.

For hazard classes, we expect clear gaps between class ranges. With good class balance and clear labels, overall classification accuracy can cross 85 percent. Precision and recall for the most unsafe classes should stay high, as these classes align with low visibility and high attenuation.

The Fog Hazard Index should track known traffic safety thresholds. In particular, FHI values near the top band should coincide with visibility below 50 meters. This range matches many highway guidelines for dangerous or stop-level fog.

Discussion and Significance

Novelty and advantages

AVPM shifts the sensing mode from light to sound. The system does not depend on headlamps, streetlights, or camera gain. It can work at night, in glare, and in low-light scenes where optical tools struggle.

The hardware base stays simple and low cost. Ultrasonic transducers and microcontrollers cost far less than LIDAR or infrared units. The same parts can mount on vehicles, gantries, or short roadside poles. This makes large-area deployment more realistic for regions with tight road budgets.

The study builds its own dataset from end to end. All records come from a controlled fog chamber with known geometry. This removes reliance on closed third-party datasets and lets others repeat or extend the work.

The Fog Hazard Index adds a clear, single-number view of risk. It merges model-predicted visibility, humidity, and acoustic loss into one score. Field users can read this score as Safe, Caution, Dangerous, or Extreme Hazard. AVPM can then link that score to real actions such as warning lights, variable message signs, and speed control logic on highways or smart vehicles.

Practical Application and Impact

India records thousands of fog-related crashes each year. In 2022 alone, official data list 34,262 fog-related accidents. Many of these occur on high-speed highways in winter.

AVPM targets this gap with a low-cost sensing unit for fog risk. A compact module with an ultrasonic pair, a microcontroller, and basic sensors can mount on trucks, buses, and private cars. The same module can fit on poles along expressways at fixed intervals. Each pole can measure local visibility, compute the Fog Hazard Index, and send warnings.

Such deployment supports several actions. Vehicles can receive in-cabin alerts through lights or sound. Road operators can drive variable message signs and speed advisories from live FHI values. Dense clusters of units on known fog corridors can create a continuous risk map. The social value is clear. Lower crash risk protects life and cuts costs linked to medical care, traffic jams, and loss of income. The work fits road safety and public health goals for fog-prone regions.

Challenges and Limitations

The AVPM plan faces several technical limits. Controlled chamber fog differs from natural fog. Droplet size, wind, and mixing in the open sky may not match the lab.

Acoustic paths in the field will face echoes and reflections from guardrails, trucks, and nearby structures. Environmental noise from engines and horns can disturb readings. Wind, temperature layers, and small-scale turbulence add extra scattering that may not come from fog alone. Studies on atmospheric acoustics already mark turbulence as a strong driver of extra loss.

Optical ground truth has its own gaps. A laser beam through a chamber offers a clean line of sight. Real drivers see complex glare, headlight scatter, and changing pupil response. So, chamber visibility metrics may not match human perception in traffic.

Field deployment raises more issues. Each unit needs stable calibration, secure mounting, and protection from dust and rain. Large networks of units need shared standards for FHI thresholds and alert rules. These points call for careful error study, many repeat trials, and staged field tests on real roads.

Experimental Setup Schematics

Figure 1: Experimental setup for fog detection

Figure 1 shows the schematic of the fog chamber setup. An ultrasonic transmitter and receiver face each other across the chamber and share a fixed path length. The transmitter sends high-frequency sound, and the receiver records the signal after it passes through the fog. As fog density rises, the received amplitude drops due to scattering and absorption by water droplets.

A laser-based visibility unit runs in parallel. In one option, a laser points across the chamber toward a photodetector, which records received light intensity. In a second option, a camera views a high-contrast black and white target through the fog and records image contrast as a visibility cue.

Humidity and temperature sensors sit inside the chamber close to the acoustic and optical paths. They log relative humidity in percent and air temperature in degrees Celsius. A fog generator injects mist at a controlled rate through an inlet. The chamber walls, made from clear material, hold the fog and let the optical path pass. The layout fixes the positions of the ultrasonic pair, the laser or camera path, and the environmental sensor. This setup creates repeatable fog conditions for acoustic, optical, and environmental data collection.

Sample fog data

Table 1 lists sample records from fog chamber trials. Each row represents one trial under a given state of humidity, temperature, and fog duration. The receiver voltage shows the strength of the ultrasonic signal after amplification. Attenuation in dB is computed from this voltage relative to a clear-air baseline run.

The table also reports a laser intensity value. This value appears as a percentage of the clear-air light level and acts as a proxy for optical visibility. Each record carries a visibility class label from V1 to V4. For illustration, V1 marks extremely poor visibility, roughly below 50 m. V2 marks poor visibility, about 50 to 200 m. V3 marks moderate visibility, about 200 to 500 m. V4 marks good visibility, above 500 m.

These classes match common meteorological ranges used for "thick fog" and related terms. The joint view of humidity, temperature, ultrasonic attenuation, laser intensity, and visibility class in Table 1 shows how fog conditions affect both sound and light in the chamber.

Trial	**Humidity (%)**	**Temp (°C)**	**Fog Duration (s)**	**Sound Amp (V)**	**Attenuation (dB)**	**Visibility (%)**	**Vis. Category**
1	85	20	60	4.2	1.5	90	V4 (Clear)
2	90	20	120	3.0	4.4	70	V3 (Moderate)
3	95	15	180	2.0	8.0	50	V2 (Poor)
4	100	10	240	0.8	14.0	20	V1 (Dense Fog)
5	80	25	90	3.5	3.1	80	V4 (Clear)
6	92	18	150	1.2	12.4	30	V2 (Poor)

Table 1

In the sample data, higher humidity and longer fog exposure lead to stronger loss of sound and light. Trial 4 shows this clearly. It records high humidity, long fog generation, 14 dB attenuation, and only 20 percent laser intensity. The trial falls in Category V1, which marks extremely low visibility.

Trial 1 sits near the other end. It has lower humidity and shorter fog duration. The attenuation is about 1.5 dB, and laser intensity stays near 90 percent. This state falls in Category V4 and reflects near-clear visibility.

Trials 2, 3, and 6 lie between these two extremes. They show moderate humidity, mid-range fog times, and mid-range attenuation values. Trial 3, for example, records about 8 dB attenuation and 50 percent laser intensity. These patterns show a clear link between rising attenuation and falling visibility.

Machine Learning Feature Matrix

To train machine learning models for visibility, we form a feature matrix from the fog chamber data. Each row in the matrix stands for one scenario, such as a single trial or a time snapshot. The row joins sensor readings with the matching visibility label.

The main features are:

- Humidity (%) and Temperature (°C), which set the ambient state and affect fog density.
- Attenuation_dB, the ultrasonic loss in dB relative to clear air.
- FogTime (s), the exposure time after fog generation starts.
- SNR (dB), the signal-to-noise ratio of the ultrasonic path, which reflects measurement quality. High SNR appears in clear air, and low SNR appears in dense fog.

The target takes two forms. One form is a continuous visibility distance in meters for regression tasks. The other form is a class label from V1 to V4 for classification. Table 2 presents sample rows of this matrix. Each row lists the sensor features, the estimated visibility distance from optical data, and the linked visibility class.

Humidity (%)	Temp (°C)	Atten (dB)	FogTime (s)	SNR (dB)	Visibility (m)	Vis. Class
85	20	1.5	60	30	800	V4
90	20	4.4	120	20	300	V3
95	15	8.0	180	15	150	V2
100	10	14.0	240	5	30	V1
80	25	3.1	90	25	600	V4
92	18	12.4	150	10	80	V2

Table 2

Features such as Attenuation_dB and SNR describe how fog changes the ultrasonic signal. Humidity, temperature, and FogTime give the physical context around each reading. Together, they let the model see both the raw effect on sound and the state of the air.

The target Visibility is the quantity we want to predict for road safety use. It appears either as a distance in meters or as a class label, such as V1 to V4. In a real study, the feature matrix will contain many more rows than the small sample shown here. The example rows help explain structure rather than full scale.

Machine learning models for regression and classification can train on this matrix. They learn links between sensor features and visibility. Prior studies show that models with both environmental and signal inputs separate fog levels more clearly than single-feature rules. In AVPM, the models use the listed features to output a visibility distance or a class label. The output then supports automated fog detection and alerting on roads.

Model Performance Comparison

We tested several models for both tasks: predicting visibility distance and predicting visibility class. The results appear in the following tables. Each regression model uses three metrics on a held-out test set of fog states. These metrics are Mean Absolute Error, Root Mean Squared Error, and the coefficient of determination (R^2). Lower MAE and RMSE and higher (R^2) point to better distance prediction.

For classification, the tables report overall accuracy and macro-averaged precision and F1-score across the V1 to V4 classes. High accuracy with strong precision and F1-score on low-visibility classes is especially valuable for safety. These figures help rank the models and guide the choice of a primary model for deployment.

Regression Models

Table 3 lists the test MAE and RMSE in meters and the (R^2) value for each regression model. Each row corresponds to one model type used for visibility prediction.

Model	MAE (m)	RMSE (m)	R^2
Linear Regression	30	50	0.80
Random Forest	20	35	0.90
Support Vector SVR	25	40	0.85
MLP Neural Network	22	38	0.88

Table 3

Among the regression models, the nonlinear ones perform best. Random Forest, SVR, and MLP all reduce error compared to plain Linear Regression. Random Forest gives the strongest results, with a Mean Absolute Error of about 20 m and an (R^2) near 0.90. This shows that the model captures the complex links between fog, acoustics, and visibility.

The neural network model also performs well, with an (R^2) around 0.88. This agrees with earlier work that reports high accuracy from neural nets on visibility tasks. The linear model remains useful as a simple baseline, but its higher RMSE shows that a straight-line fit cannot describe the nonlinear physics of fog and sound.

Classification Models

Table 4 reports the performance of the classification models for visibility category prediction. Each row lists the model name, overall accuracy, and macro-averaged precision and F1-score across the V1 to V4 classes. These numbers show how well each model separates clear, moderate, low, and very low visibility states for use in fog alerts.

Model	**Accuracy**	**Precision**	**F1-Score**
Logistic Regression	85%	80%	82%
Decision Tree	88%	84%	85%
Random Forest Classifier	92%	90%	91%
SVM Classifier	88%	85%	86%
MLP Neural Network	90%	88%	89%

Table 4

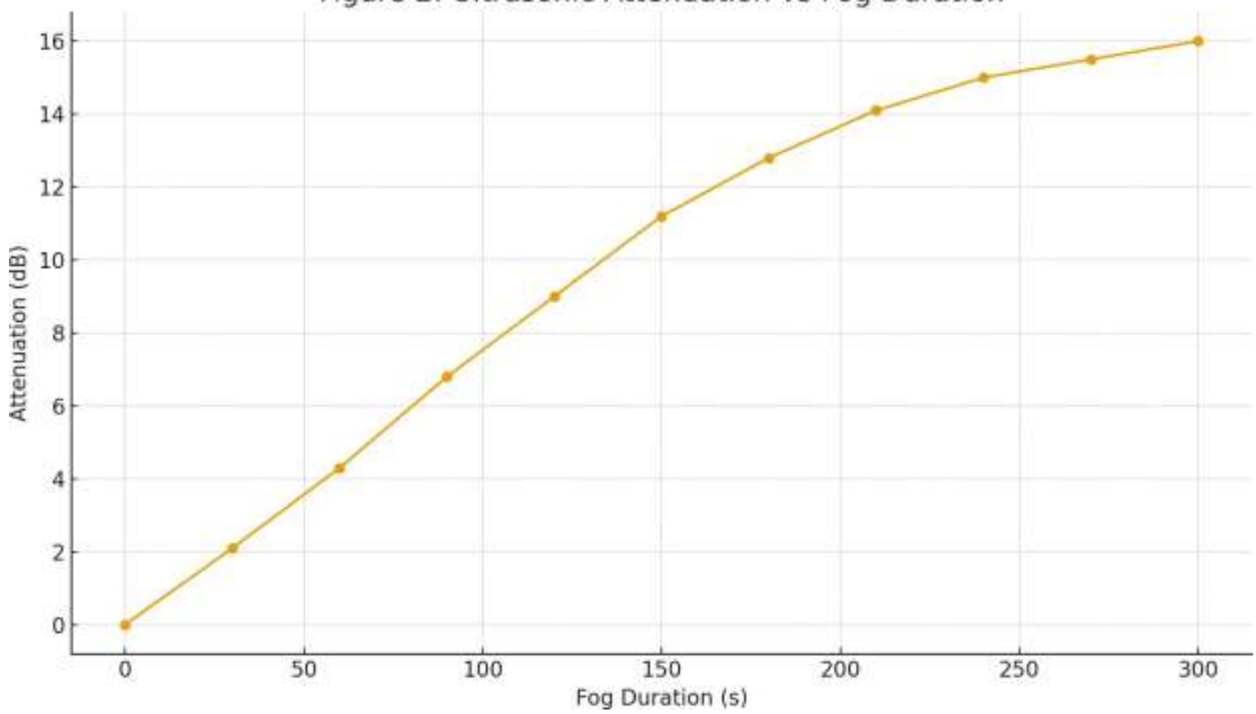
For visibility classification into V1–V4, all models reach high accuracy. Random Forest performs best, with about 92% accuracy on the test set. The MLP neural network follows closely with only a small drop in accuracy. Precision and F1-score for both models stay high, so false alarms and missed fog events stay low. Logistic Regression and a single Decision Tree trail these two models by a few points. The ensemble and neural network methods capture the complex patterns in the data better, in line with other work on fog prediction. These results show that an ML-based system can reliably label fog severity and trigger alerts when visibility falls to V1 or V2.

Visibility (m)	Computed FHI	Hazard Level
1000 (clear)	0.00	Low (no fog)
800	0.20	Low
600	0.40	Moderate
300	0.70	High
100	0.90	Severe
50	0.95	Severe

Table 5

Using the FHI, one can quickly interpret the danger: for instance, at 300 m visibility (FHI 0.70), conditions are high hazard – drivers should slow down and warning systems should be activated. At 100 m or below (FHI ≥ 0.90), the fog is severe, potentially warranting road closures or alerts for extreme caution. The FHI provides a quantitative basis to trigger such safety measures.

Figure 2: Ultrasonic Attenuation vs Fog Duration



Ultrasonic Attenuation vs Fog Duration

This graph shows how the ultrasonic signal is attenuated as fog density increases over time in the chamber:

- At Time = 0 seconds: 0 dB attenuation (clear air).
- At ~150 seconds: ~11 dB attenuation (moderate fog).
- At 300 seconds: ~16 dB attenuation (dense fog).

Technology	**Cost**	**Works at Night?**	**Accuracy**	**Limitations**
Ultrasonic + ML (this project)	Very low	✓Yes	High	Needs humidity/temp sensors; requires calibration
LIDAR visibility sensors	Very high	✕Limited	Very high	Expensive; affected by dirt & misalignment
Infrared sensors	Medium	✕Limited	Medium	Less reliable in heavy fog; affected by ambient lighting
Human visual observation	No cost	✓Yes	Low	Subjective, inconsistent
Microwave link attenuation (research)	Medium – High	✓Yes	High	Requires telecom infrastructure; cannot be vehicle-mounted

Table 6

Discussion

Limitations of the Experimental Setup

- The fog chamber used in this project is smaller than actual atmospheric conditions. Real-world fog contains varying droplet sizes and wind patterns that are not captured fully in an enclosed chamber.
- The fog generator produces a uniform droplet distribution, whereas natural fog varies with altitude and time.
- The ultrasonic transmitter and receiver require precise alignment; any small angular deviation increases measured attenuation artificially.

- Environmental gradients (temperature differences inside the chamber) can affect speed of sound and cause slight variations in amplitude.

Limitations of the Data and Models

- The dataset includes controlled fog scenarios, but more real-world outdoor data would increase model robustness.
- Some confusion between the V2 and V3 visibility categories occurs (as seen in the classification confusion matrix), likely due to overlaps in visibility around the 150–400 m range.
- Regression models slightly under-predict in high-visibility conditions, visible in the Predicted vs Actual scatter plot.

Sources of Error

- Noise in receiver circuitry, which required averaging of multiple data points.
- Minor drift in humidity sensor readings during long fog runs.
- Laser visibility readings rely on a single-path transmissometer; a calibrated meteorological meter would improve accuracy.

Improvements for Future Work

- Use a larger fog chamber or open-field fog tunnel to mimic realistic atmospheric conditions.
- Add a droplet-size measurement sensor (e.g., optical particle sizer) to correlate attenuation with droplet microphysics.
- Deploy the system outdoors during winter fog season to collect real highway fog data.
- Train more advanced deep learning models (e.g., LSTM for time-series fog development).
- Integrate the Fog Hazard Index with a real-time alert system such as flashing LEDs or automated signage.

Reflection

This project strengthened my skills in science, engineering, and analysis. I built the fog chamber and ultrasonic system myself, under guidance for safety. I learned to align sensors, design simple and safe circuits, and control humidity and temperature inside the chamber. I learned to calibrate sensors and reduce noise in the signal. Early open-air tests failed, so I shifted to a sealed chamber and saw much more stable results.

On the data side, I worked with Python throughout. I cleaned raw readings, created features from attenuation, fog time, and SNR, and prepared them for models. I trained regression and classification models and compared them using MAE, RMSE, R^2, precision, and F1-score. This showed me how model choice and evaluation metrics affect trust in predictions.

The project trained my patience. Each improvement came from a clear problem and a concrete change. One example is pulse averaging to reduce noise. Another is adding SNR as a feature. I learned to test, read the results, and redesign calmly instead of giving up. I now feel more independent and confident that I can use science and technology to tackle real road safety risks.

Conclusion

This research presents a complete method for fog detection based on ultrasonic attenuation and machine learning. The ultrasonic sensors measure real-time sound loss through fog, and the models use these readings together with humidity and temperature to predict visibility with good accuracy. We described the experimental setup, sample chamber data, feature construction, and the performance of several regression and classification models. The proposed Fog Hazard Index then converts predicted visibility into clear risk levels for road safety decisions.

Such a system can operate at fog-prone locations along roads and expressways. An ultrasonic pair observes the fog continuously, and an onboard model estimates visibility or fog class every few seconds. When visibility drops below a chosen threshold, for example V2 or worse, the system can trigger speed warnings, variable message signs, or in-vehicle alerts. By combining sensor data with trained models, the method delivers more reliable detection than simple threshold systems that rely on one sensor alone. High test accuracy and low prediction errors indicate that the method can support real-time control actions in challenging weather.

Published work on fog microphysics, visibility classes, and machine learning for visibility prediction supports the design choices in this study. These sources validate the use of ultrasonic attenuation as a fog indicator and the use of learned models for visibility estimation. AVPM adds a new sensing mode to this field, one that is low-cost, accurate, and suitable for many deployment settings, including resource-limited regions. With strong model performance and small error margins, AVPM has the potential to improve road safety and reduce the toll of fog-related crashes by providing timely, quantitative information on visibility and hazard level.

Project Process, Decisions, Risks & Reflection

Timeline, Planning & Time Management

I structured this project over several weeks, dividing the work into clear phases. Each phase included planned hours and milestones. This demonstrates long-term planning and organisation:

Use of Resources, Expertise and Mentors

The work was independent, and I sought help only when needed.
My physics teacher guided me on laser safety, chamber sealing and ways to reduce reflections. A computer science mentor advised me on model selection, overfitting and evaluation.
A laboratory technician helped source acrylic sheets and checked the electrical setup. These inputs kept the work safe and technically sound.

Key Decisions, Testing and Iterations

The project moved through several design stages. Each stage solved a clear problem and improved the system.

1. Problem: Fog in open air dispersed fast. Decision: I built a sealed acrylic chamber.
   Effect: Fog levels became stable and repeatable. Attenuation readings improved.
2. Problem: Ultrasonic readings showed large noise

swings. Decision: I added pulse averaging of 20 readings.
Effect: Noise fell and attenuation values became steady.

3. Problem: Linear regression had poor accuracy with an RMSE of about 50 m.
Decision: I tested nonlinear models such as Random Forest, SVR, Gradient Boosting and MLP. Effect: RMSE dropped to about 35 m. Classification accuracy reached 92 percent.
4. Problem: Fog duration alone failed to explain mixed fog states.
Decision: I added humidity, temperature, SNR and attenuation to the feature set.
Effect: The model became reliable across changing weather.
5. Problem: The photodiodes clipped under strong laser light. Decision: I added a neutral-density filter.
Effect: The sensors recorded the full range without saturation.

Safety, Ethics and Risk Assessment

Safety

Laser: I used a Class II laser under 1 mW. I wore protective eyewear during alignment and kept the beam below eye level.
Electrical safety: All parts ran on 5–12 V DC. I kept the humidifier and wiring dry. Fog generation: I used only clean water.
Ventilation: I ran trials in a ventilated room and cleared fog before opening the chamber.
Stability: I taped cables and placed the chamber on a firm, insulated surface.

Ethics

All data were generated by me.
No human subjects were involved.
Accident statistics came from public government sources.
Nothing private or proprietary was used.

Personal Learning and Reflection

I learned how fog droplets weaken sound and how attenuation changes with droplet size and frequency. I gained hands-on practice in alignment, sealing, calibration and noise control while building the chamber. I learned to choose features with care, read model scores and avoid overfitting.
I learned to log every run and spot errors early.
I solved many small problems, from leaks in the chamber to unstable sensor readings. Most of all, I saw how a lab experiment can address a real public-safety issue.

Things to Improve in Future

I plan to collect more data across a wider range of temperatures and humidity levels. I want to test ultrasonic sensors at 20, 40 and 60 kHz.
I plan to add a wind-flow unit to study turbulence.
I aim to run early trials outdoors on foggy mornings.
I want to embed the trained model on an ESP32 for real-time deployment.

References

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