Analysis of road accidents due to obstruction in sight distance caused by foggy weather using Geographic Information System (GIS) and Artificial Neural Network (ANN) at Jumja along Thimphu-Phuentsholing Highway (Asian Highway 48).

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Abstract.

Road accident analysis is a crucial technique for determining what elements contribute to collisions and can help lower the accident rate. The consideration of sight distance is a crucial component of highway geometric design in order to guarantee effective traffic operations with the highest level of safety at an affordable price. Road accidents frequently result from reduced visibility caused by foggy weather, hence there is increased interest in studying this issue. This study aims to determine and correlate sight distance, fog blockage, and their effects on traffic accidents at Jumja along Thimphu-Phuentsholing Highway (Asian Highway 48). Data gathering and prediction was aided by the usage of Geographic Information Systems and Artificial Neural Network technologies. Temperature, relative humidity and wind speed for seven years from 2017 to 2023 were considered for fog occurrence to train Artificial Neural Network. Visibility was trained and predicted for summer and winter seasons since the occurrence of fog is prevalent during these seasons. As a result, a correlation value R of 0.998 was found, proving the findings to be almost accurate. This study offers a thorough investigation of how sight distance contributes to traffic accidents at Jumja region. A conclusive finding addressing the significance of sight distance as a contributing factor to traffic accidents due to fog invisibility along Jumja region was made after completion of this study.

Keywords: Sight Distance, Foggy Weather, Road Accidents, AH48 Highway, Geographic Information System, Artificial Neural Network.

Introduction.

Snow- or rain-related collisions have been the subject of research on weather's impact.

However, crashes that happen in fog or smoke (FS) are not well understood (Abdel-Aty et al., 2011). A cloud layer that arises near to the ground because of microscopic water droplets or ice crystals floating in the air is a phenomenon known as fog. Fog lowers vision, making it challenging for pedestrians, pilots, and cars to see nearby objects. The dew point, or the temperature at which the air becomes saturated and incapable of retaining moisture, is the point at which fog typically develops. Fog is one of the reasons which obstructs visibility. One of the primary causes of accidents was poor visibility brought on by the weather while driving (Miclea et al., 2021).

Degraded road visibility has the potential to 1) catch even the experienced drivers off guard, 2) change the way that drivers behave, and 3) distort drivers' perceptions of depth, distance, and speed. Foggy weather conditions pose an immediate threat to road safety, frequently resulting in fatal road accidents (Oğuz & Pekin, 2019). All drivers, regardless of skill level, face risks when driving through fog. The capacity of a roadway can be reduced by up to 12% and travel speeds can be drastically reduced (Brooks et al., 2011).

Geometric design of highway involves the design of visible dimensions of the roadway**.** The important element of the road is directly connected to the users of the highway and is designed with that respect. The designers of highways must ensure that there are sight distances throughout the route that are long enough for the majority of drivers to handle their cars without colliding with other vehicles (Weerasekera, 2021). Ensuring that the available sight distance on a roadway matches driving demands is a crucial component of highway design. The driver will not be able to stop in time to prevent a collision if the sight distance at any point on a roadway is less than the distance needed to halt completely after spotting a danger (Gargoum et al., 2018). A vehicle should have enough sight distance to stop before it reaches stationary objects in its path while traveling at the authorized speed, which is a crucial factor in traffic safety (de Santos-Berbel et al., 2014).

For the international airport in Canberra, Australia, Fabbian et al (2007) employed the ANN approach utilizing 44 years of observational data. The model has been trained with the following parameters as inputs: temperature, dew temperature, wind speed and direction, average sea level pressure, total cloud cover, visibility, and rainfall. They therefore came to the conclusion that the model had strong predictive ability (Oğuz & Pekin, 2019). Different research (Cools et al., 2008) evaluated how the weather affected the volume of traffic. Snowfall and rain had definitive findings from this study, however, the impact of impaired visibility owing to fog and cloudiness is still unknown.

Bhutan has not conducted any research on the severity of road accidents brought on by shortened visibility due to foggy weather. This study attempts to thoroughly examine this problem and shed light on how visibility obstructions affect traffic accidents. Because no prior research has been done on how reduced visibility brought on by fog impacts road accidents in Bhutan or elsewhere, the study is essential.

Study Area.

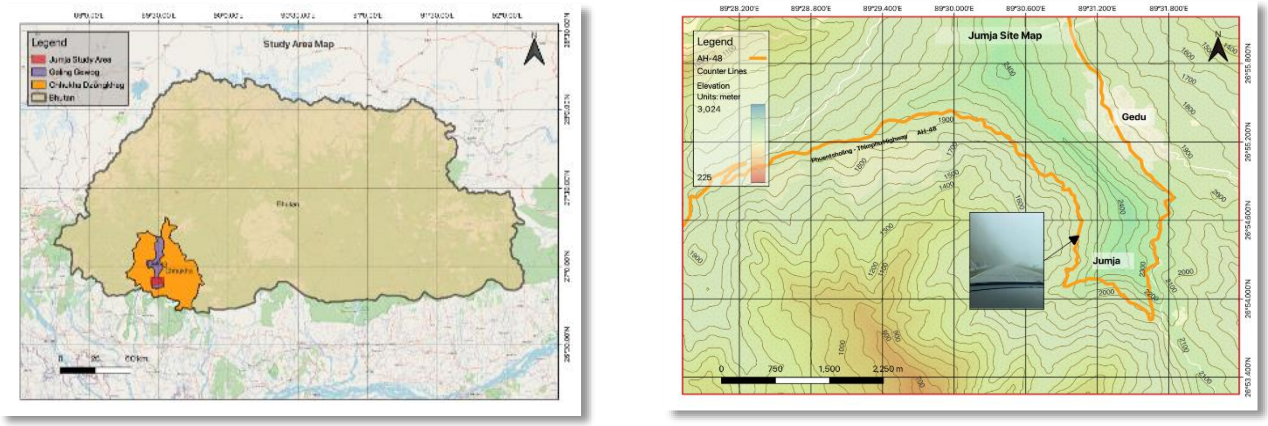
The project was carried out along Thimphu-Phuentsholing High way at Jumja region, located at Gedu, Bhutan. Gedu is a town in the southwest of the country. Jumja region was considered as the research area because it consistently has foggy weather throughout the year, making it one of the areas with the highest accident rates as shown in Figure 1. The Phuentsholing-Thimphu Asian Highway includes the Jumja region, and prior studies have shown that numerous incidents have happened there, leading to heavy traffic and a higher risk of accidents. As a result, it was decided that the research region was appropriate for creating an ANN visibility prediction tool and evaluating its effectiveness. The Figure 2 shows the (a) map of study area and (b) AH48 network between Jumja region to Gedu.

Figure 1.

Presence of Fog at Jumja region of AH48.

Figure 2.

Study Area: (a) shows the study area and (b) shows the Asian Highway Network between Jumja to Gedu.



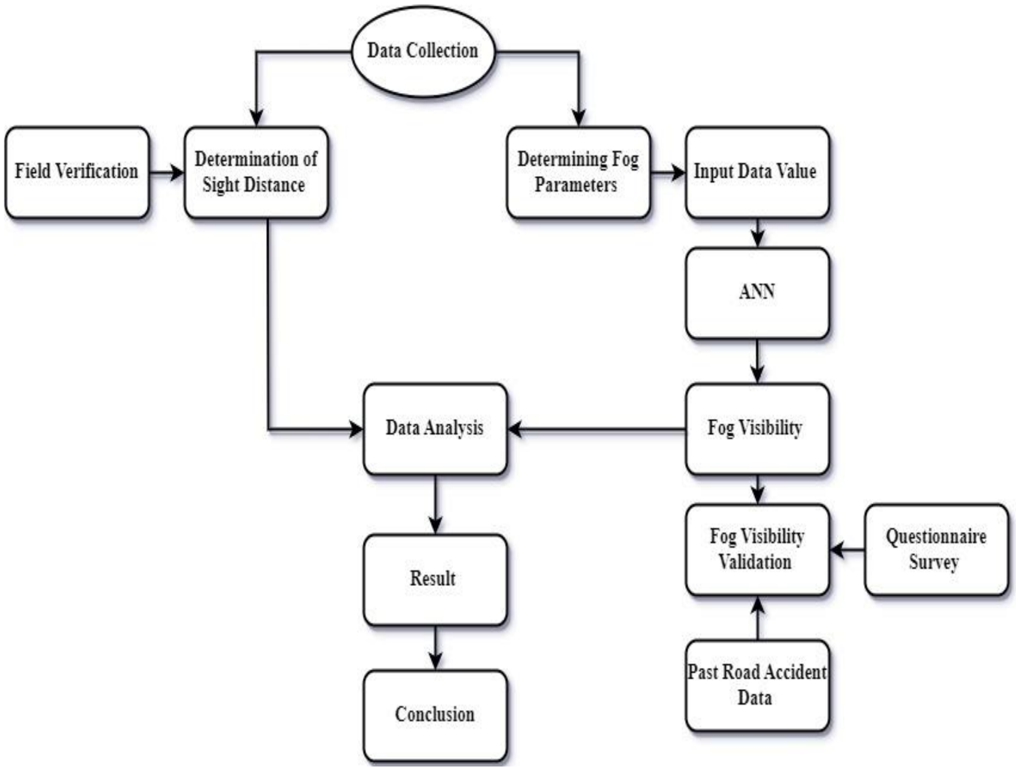
(a)

(b)

The methodology flowchart shown in Figure 3 shows the project's step process and served as the foundation for the study. The information was separated into two sets to be collected for the study. The sight distance, or the distance a motorist can see ahead on the road in various weather conditions, was determined using the initial batch of data that was gathered.

Figure 3.

Methodology flow chart



This required examining several variables, including the road grade, the radius of the curve, the speed of the car, and the stopping distance. The second batch of data was gathered to identify the necessary fog parameters for the ANN prediction model. The ANN model is a particular kind of machine learning algorithm used to forecast the likelihood of traffic accidents occurring in foggy circumstances.

Data from important atmospheric variables, such as visibility, temperature, humidity, wind speed, and others, were collected for this set of data. The study attempted to make conclusions on the link between sight distance, fog blockage, and their influence on traffic accidents along the Jumja Highway by merging these two sets of data. The methodology flowchart gave the study an organized approach, ensuring that all relevant data was gathered and correctly evaluated to meet the study's goals.

Data Processing.

Sight Distance Calculation.

The GIS was used to determine the sight distance for the Jumja Highway, which is four kilometres in length. To examine the topography and height of the road segments, a digital elevation model (DEM) of the road network was built.

The topography and height of the road segments, a DEM of the road network was developed using GIS software. To calculate the sight distance, a line of sight between the driver's eye level and a roadside object was created. This object could be a stationary vehicle or a curve in the road. It was considered that any potential roadside barriers such as trees, buildings, or other cars could block the driver's view. By creating the line of sight, the distance between the object and the driver's eye level was determined. Using the DEM, the height of the object and the driver's eye level was calculated, considering the terrain of the road network (Figure 4). By using GIS technology, accurate measurements of the sight distance was obtained (Table 1) to identify potential problem areas.

Figure 4.

Plotting Visible Points to calculate Sight Distance.

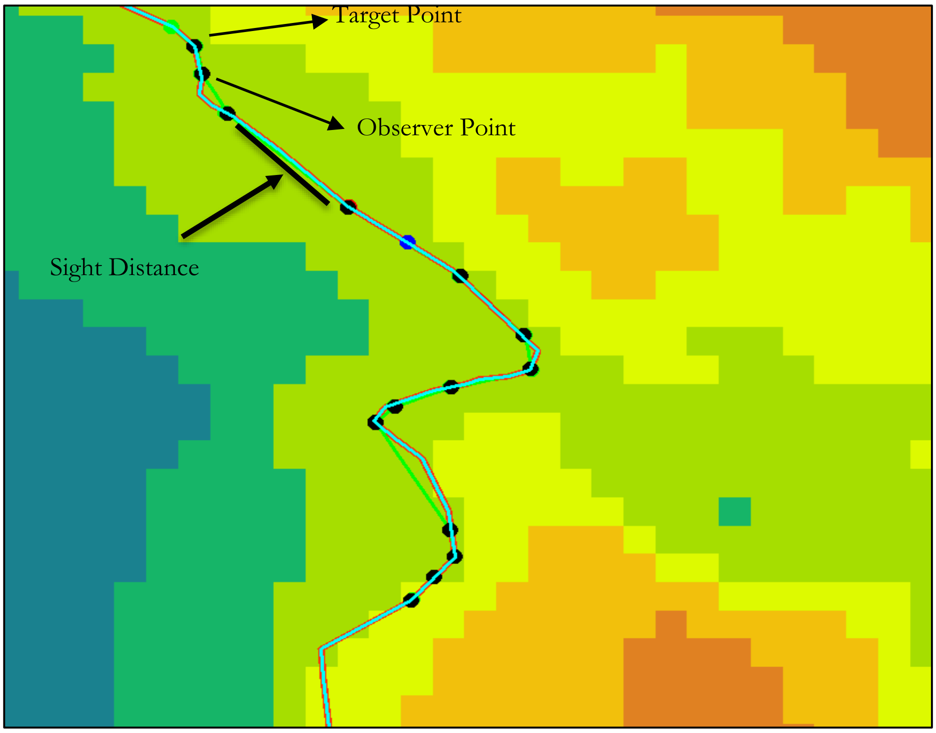


Table 1.

Sight Distance Result in Meters.

Station (Km)	Sight Distance (m)	Station (Km)	Sight Distance (m)
0.163	157.38	1.185	21.41
0.296	126.43	1.276	89.865
0.312	16.096	1.552	251.568
0.359	42.73	1.582	26.907
0.397	37.102	1.68	88.413
0.454	52.87	1.776	66.305
0.596	138.714	1.803	27.1
0.623	27.09	1.901	91.875
0.851	193.38	1.932	30.266
1.048	123.39	2.094	129.616
1.132	82.772		

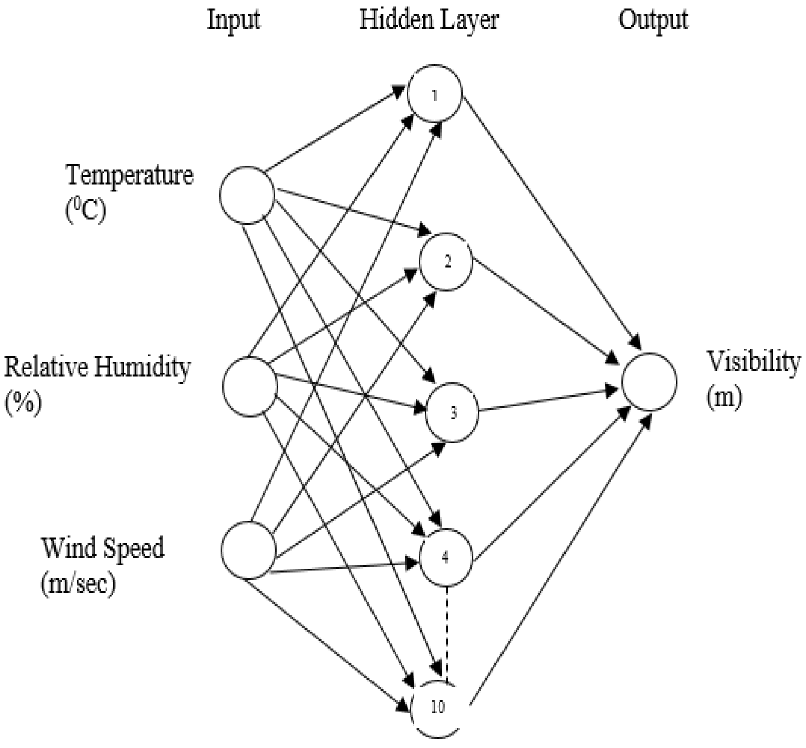
ANN Training Method.

1. ANN Scheme.

Artificial Neural Network (ANN) is a computational model inspired by the function and structure of the human brain. Each layer of the ANN has cells that allow information to be transferred from one layer to the next, establishing an interconnected network. This network is like a system of parallel layers with communication paths that connect cells and their inner workings sequentially. Figure 5 depicts the schematic depiction of ANN.

Figure 5.

ANN Scheme.

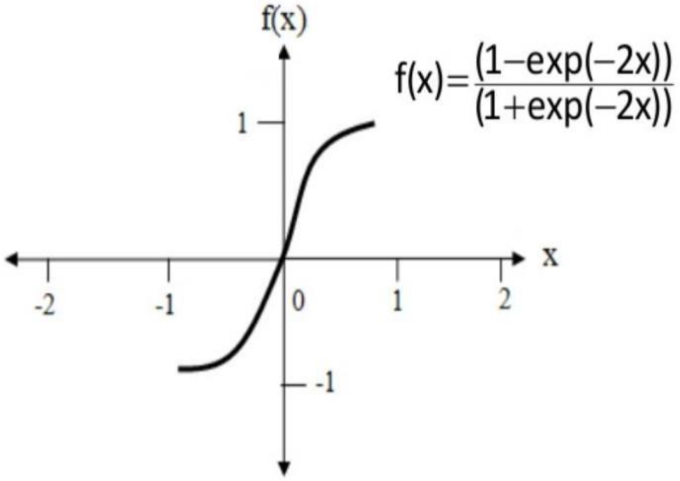


2. Activation Function.

In the study, pureline (linear) function in the output layer and tangent hyperbolic activation function (Tanh) in the training phase's hidden layer were both used. The tanh activation function creates a curved connection between the input and output units. Performance of the network is significantly impacted by the activation function choice. The sigmoid function and the tanh function are linked. This activation function's output value is frequently between [-1, 1] and [0, 1]. Almost often, this is a non-linear function. Artificial neural networks may now be used to solve a wide range of challenging problems thanks to the advent of nonlinear activation functions. Figure 6 below illustrates the bipolar tangent hyperbolic function f (x):

Figure 6.

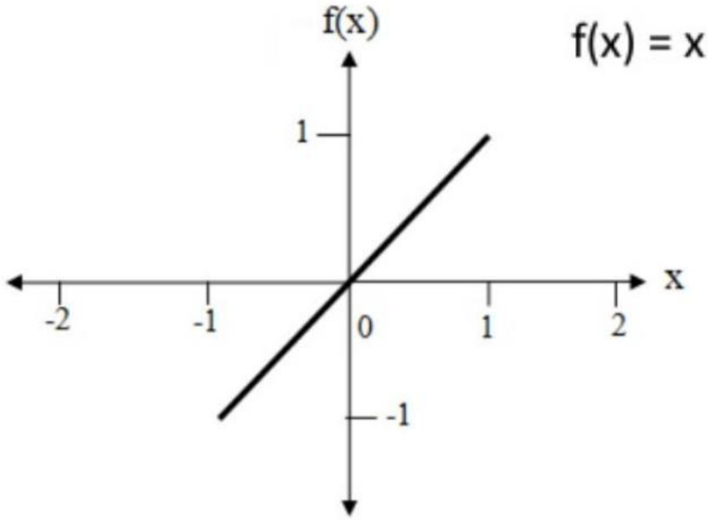
Tangent hyperbolic activation function.



In the output layer's pure line activation function, neuron output fluctuates linearly in response to changes in neuron input. The output value's possible changes fall within the range [-1 1]. Figure 7 displays the pure line activation function graph.

Figure 7.

Pure line activation function (output layer).



3. Assessment of Model Performance.

To predict the visibility, the Feed Forward Neural Network (FFNN) model was used. The FFNN neural network design is popular and well-known, and it is frequently used for supervised learning tasks like regression and classification. This particular ANN type just allows information to flow from input to output, making it simpler to comprehend and use.

4. ANN Architecture.

Table 2 presents the overall structure of the Artificial Neural Network (ANN) employed in this study. It comprises three input layers, namely temperature, relative humidity, and wind speed. The ANN consists of 10 hidden layers and produces a single output. The training process involves 51 epochs, which represent the number of times the entire dataset is iterated during training. The mean squared error, which calculates the average squared difference between anticipated and actual data, is the loss function used. The tangent hyperbolic activation function is the activation function employed by the ANN. This function is applied to each neuron in the network and helps to determine the output value based on the weighted sum of inputs. The chosen architecture and parameters aim to optimize the ANN's performance in predicting the desired output based on the input variables.

Table 2.

ANN Architecture.

Optimal Parameters	Values
Input size	3
Hidden layers	1
Hidden units	10
Output size	1
The architecture of the model	Input layer→ Feed forward neural network →Output layer
Epoch	51
Loss function	Mean Squared Error
Activation function	Tanh

Data Analysis and Visibility Prediction.

Sight Distance Validation.

After the preliminary desk research, a site inspection was carried out to guarantee the precision of the sight distance estimations. The objective of surveying was to determine the sight distance for a few particular stations along the Jumja Highway where possible issues were identified. For the survey, Total Station (Surveying Equipment) was used and coordinates of every station were recorded. At site, the horizontal curve (Figure 8) was surveyed for various sight distances.

Figure 8.

Curves surveyed.

The sight distance was then calculated using the following equation (1).

$$M_s = R_v \ (1\text{-}\cos\frac{\Delta}{2}) = R_v \ (1\text{-}\cos\frac{90\ X\ SSD}{\pi\ X\ \mathrm{Rv}}) \qquad (1)$$

Were,

R_v = Effective Depth (m).

SSD= Stopping Sight Distance (m).

Ms= Sight Distance (m).

Δ = radius of the curve (m).

The measured sight distances were then compared to the calculated values obtained from the desk work using the GIS software. Any significant discrepancies between the surveyed and GIS measured data were review for error. By validating the sight distance calculations through a site survey, it ensured the accuracy of the results and any potential issues that might have been missed during the desk work. This information was crucial in developing targeted interventions to improve road safety and analyse the likelihood of accidents.

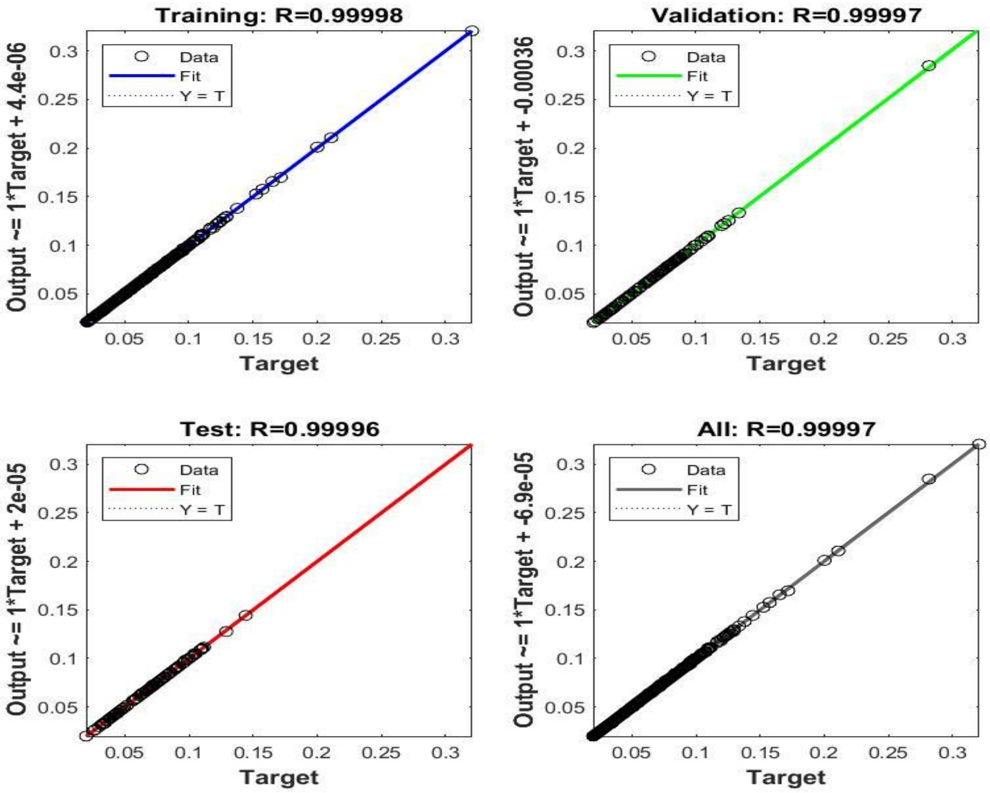
Results.

Coefficient of correlation (R).

The correlation coefficient plot in Figure 9 illustrates the strength of a linear link between the predicted and observed values. With a coefficient of correlation of 0.99998 for training, 0.99997 for validation, and 0.99996 for testing, the model generated the best-fit regression. The average correlation coefficient of 0.99997 shows that the input and output values have a close relationship, making ANN an excellent choice for visibility prediction.

Figure 9.

Regression Plot strength of a linear link between the predicted and observed values.



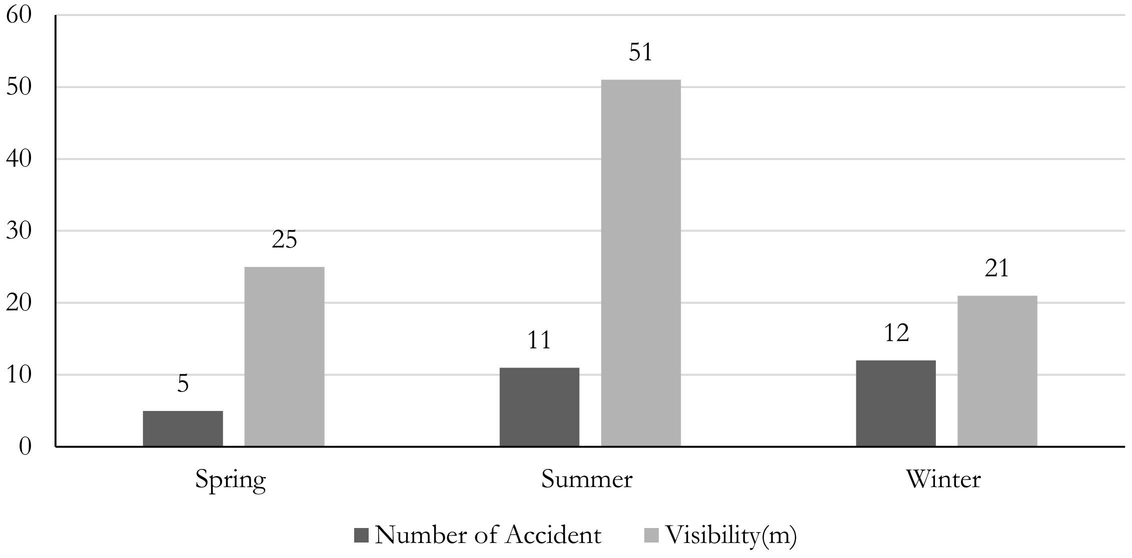
Number of accident versus visibility for different season.

According to statistics gathered from Royal Bhutan Police (RBP), Chukha, accidents occurred more frequently in the winter and summer months when fog presence was higher (Figure 10). This implies a direct link between the incidence of accidents and the presence of fog. The relative humidity rises throughout the winter because of the large drop in temperature. Fog develops as a result, which can impair vision and raise the possibility of accidents. The same is true during the summer, when a combination of warm air and high humidity can result in the creation of fog.

Fog may severely limit a driver's sight, making it challenging for them to notice objects and other cars on the road. Accidents can result from this decreased vision, particularly if cars are moving quickly or if there aren't any markers or signs on the road to direct them.

Figure 10.

Number of accident versus visibility during different seasons.



Discussion.

Sight distance was calculated using GIS software, allowing analytical tools and geographic data to be used for geospatial research. It aided in the accurate measurement and visualization of several spatial parameters, including topography, elevation profile, and road alignment, which are essential for calculating sight distance. Utilizing survey equipment, the calculated visual distance was validated. The results showed little fluctuation and were judged acceptable.

An ANN model, a machine learning technique, was used to predict visibility. By contrasting anticipated and observed visibility levels, the model's accuracy was evaluated. The correlation coefficient, a statistical measure of how strongly two variables are correlated linearly was discovered to be 0.9998, suggesting a highly significant positive association. Due to the ANN model's strong correlation coefficient, visibility values in many scenarios including those with variable topography, terrains, and weather patterns were correctly predicted.

However, it was found that certain stations failed to maintain the necessary minimum sight distance of 60 meters at a speed of 50 kmph, particularly because of the obstacle brought on by fog, which decreases visibility and raise the risk of accidents. Fog was more prevalent and evident throughout the summer and winter seasons, according to road users and data analysis. Additionally, it was shown that accidents were more frequent in these foggy seasons. The study came to the conclusion that accidents at these times were strongly impacted by the limited visibility due to presence of fog.

Conclusion.

To enhance the accuracy of the prediction model, incorporating more data with additional variables such as pressure and rainfall is essential. It is also beneficial to consider a larger stretch of the road, including sight distance of all stations, to make the study more effective. The ANN model proves to be a reliable tool for predictions, providing small deviations from actual data as long as the input data is precise. This accuracy makes it valuable for road planning and forecasting fog visibility in Bhutan or other routes, eliminating the need for manual calculations.

One unique aspect of this research was examining the correlation between fog presence and traffic accidents, which lacked prior studies or empirical data for comparison or validation. This presented a significant challenge during the study, requiring innovative data gathering and analysis methods. The absence of established frameworks made it difficult to develop precise research instruments, such as questionnaires, surveys, and the ANN model, while also hindering identification of potential biases or errors.

This study underscores the importance of conducting original research in areas with limited existing studies, despite the challenges involved. It can aid stakeholders and policymakers in understanding new issues and providing practical solutions to mitigate risks. Future researchers can build upon this work by conducting related investigations, constructing forecasting models for highways that consider all stations over longer distances. By incorporating data for up to a year, these models can inform more extensive studies and planning. Leveraging Closed Circuit Television (CCTV) and precise technologies would also streamline data collection, replacing laborious manual approaches.

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Reference.

Abdel-Aty, M., Ekram, A. A., Huang, H., & Choi, K. (2011). A study on crashes related to visibility obstruction due to fog and smoke. *Accident Analysis & Prevention, 43(5),* 1730–1737. https://doi.org/10.1016/j.aap.2011.04.003

Ansari, S., Akhdar, F., Mandoorah, M., & Moutaery, K. (2000). Causes and effects of road traffic accidents in Saudi Arabia. *Public Health*, *114*(1), 37–39. https://doi.org/10.1038/sj.ph.1900610

Brooks, J. O., Crisler, M. C., Klein, N., Goodenough, R., Beeco, R. W., Guirl, C., Tyler, P. J., Hilpert, A., Miller, Y., Grygier, J., Burroughs, B., Martin, A., Ray, R., Palmer, C., & Beck, C. (2011). Speed choice and driving performance in simulated foggy conditions. *Accident Analysis and Prevention*, *43*(3), 698–705. https://doi.org/10.1016/j.aap.2010.10.014

Castro, M., Iglesias, L., Sánchez, J. A., & Ambrosio, L. (2011). Sight distance analysis of highways using GIS tools. *Transportation Research Part C: Emerging Technologies*, *19*(6), 997–1005. https://doi.org/10.1016/j.trc.2011.05.012

Cools, M., E. Moons, and G. Wets, (2010). Assessing the Impact of Weather on Traffic Intensity. *Weather, Climate and Society., 2,* 60–68, https://doi.org/10.1175/2009WCAS1014.1.

de Santos-Berbel, C., Castro, M., Medina, S. L.-C., & Paréns-González, M. (2014). Sight Distance Studies on Roads: Influence of Digital Elevation Models and Roadside Elements. *Procedia - Social and Behavioral Sciences*, *160*, 449–458. https://doi.org/10.1016/j.sbspro.2014.12.157

Eshragh, F., Pooyandeh, M., & Marceau, D. J. (2015). Automated negotiation in environmental resource management: Review and assessment. *Journal of Environmental Management*, *162*, 148–157. https://doi.org/10.1016/j.jenvman.2015.07.051

Fabbian, D., R. de Dear, and S. Lellyett, (2007). Application of Artificial Neural Network Forecasts to Predict Fog at Canberra International Airport. *Weather and Forecasting,* 22, 372–381, https://doi.org/10.1175/WAF980.1.

Gargoum, S. A., Tawfeek, M. H., El-Basyouny, K., & Koch, J. C. (2018). Available sight distance on existing highways: Meeting stopping sight distance requirements of an aging population. *Accident Analysis and Prevention*, *112*(December 2017), 56–68. https://doi.org/10.1016/j.aap.2018.01.001

Miclea, R. C., Ungureanu, V. I., Sandru, F. D., & Silea, I. (2021). Visibility Enhancement and Fog Detection: Solutions Presented in Recent Scientific Papers with Potential for Application to Mobile Systems. *Sensors, 21*(10), 3370. https://doi.org/10.3390/s21103370

Oğuz, K., & Pekin, M. A. (2019). Yapay Sinir Ağları ile Esenboğa Havaalanı için Sis Görüş Mesafesinin Tahmin Edilebilirliği. *European Journal of Science and Technology*, *15*, 542–551. https://doi.org/10.31590/ejosat.452598

Wangdi, C., Gurung, M. S., Duba, T., Wilkinson, E., Tun, Z. M., & Tripathy, J. P. (2018). Burden, pattern and causes of road traffic accidents in Bhutan, 2013–2014: a police record review. *International Journal of Injury Control and Safety Promotion*, *25*(1), 65–69. https://doi.org/10.1080/17457300.2017.1341930

Weerasekera, K. (2009). Introduction to highway design. In *An Elementary Highway Design.* (1st ed.).