Machine Learning Approach to Predict the Accident Risk during Foggy Weather Conditions

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Abstract- Vehicle mishaps in foggy climate conditions have expanded in the proper method of time. One of significant reason is contamination rate has expanded in the earth we are seeing a dynamic difference in atmosphere independent of seasons. Visibility level gets decreased because of foggy climate conditions is a typical factor for street mishaps on roadways. This subsequently there has been an expansion of interest to build up a smart framework which can keep away from/mishaps or smashing of vehicles from behind utilizing a visibility go estimation framework. The framework would caution the driver if there is any obstruction before the vehicle. In this paper, we give a short outline of the best in class commitment in connection to assessing visibility separate under foggy climate conditions. We at that point present a neural system approach for evaluating visibility separations utilizing a camera that can be fixed to a street side units (RSU) or mounted locally available a moving vehicle or long separation Sensors .The proposed strategy can be made as inherent item for 4 wheeler or more vehicles which make the vehicle clever.

***Index Terms**:* Visibility Distance; Fog Detection; Intelligent Transportation Systems; Neural Networks; Machine Learning ; Koschmieder Law; Computer Vision ;Road Accident.

I INTRODUCTION

Foggy climate conditions speak to an up and coming risk to street wellbeing, frequently prompting lethal street mishaps on the grounds that debased street visibility can possibly (1) shock even experienced drivers, (2) adjust the drivers' driving conduct, and (3) mutilate drivers' view of profundity, separate, and speed[1].

These issues have caused gigantic financial misfortune just as human setbacks. As indicated by Global Status Report on Road Safety, distributed by World Health Organization in 2015, about 1.25 million individuals were executed and 20-50 million people groups got injured non-deadly wounds (WHO report, 2015) consistently.

As per the street auto collision information given by states, Delhi records one of the most astounding number of deadly mishaps (NHAI report, 2016). Street auto collision recorded information is acquired from National Highway Authority of India (NHAI). Not with standing, this pattern can change in future as it is difficult to anticipate the rate at which street auto collisions happen as it can happen in any circumstance.

Prior research[1,2,3] uncovered that albeit foggy climate conditions are not intermittent marvels, the quantity of related various impacting vehicles, wounds and fatalities are a lot higher than normal.

Since thruway mist reduction advances have not come to yet the ideal dimension of development and financial feasibility, a few roadway crash countermeasures and new vehicle plan innovations have been proposed to help drivers adapt to foggy climate conditions. These incorporate reflectorized paints on asphalt edge striping, beaded path delineators, squinting strobe lights, and installed hardware including haze lights, Light Detection and Ranging (LiDAR) sensors and Autonomous Emergency Braking (AEB) frameworks, among numerous others.

II RELATED WORK

1) **Identification of Traffic Accident Trigger:** Tremendous endeavors have been given to the recognizable proof of key conditions or specific traffic designs that could prompt car crash. For example, Oh proposed the supposition that problematic traffic stream is a trigger to crash [4].

2) **Real-time Traffic Accident Prediction**: With the improvement of AI, numerous specialists begin to concentrate on constant car crash forecast. Lv picked highlight factors dependent on Euclidean measurement and used k-closest neighbor technique to anticipate auto collision [5].Park gathered enormous car crash information of thruway in Seoul and fabricate an expectation work process dependent on k-implies bunch investigation and calculated relapse [6]. One impediment of these works is that, they didn't consolidate a few significance factors, for example, traffic stream, climate condition, air quality into their model.

3) **Deep Learning:** The achievement of profound learning has demonstrated its capacity in finding mind boggling structures in high dimensional information. With respect to explores on insightful transportation framework, various investigations center around traffic stream forecast dependent on profound learning [7]. In a more drawn out time scale, a few examinations attempt to anticipate the blockage development of vast scale transportation arrange [8]. Another fascinating application used profound fortification figuring out how to control the planning of traffic flag [9].

Mist definition and visibility models

Mist is a sort of cloud on the ground and is shaped by the suspension of tiny dampness dewdrops into airborne particles. As per the Meteorological Office 1969[10], mist is characterized as the condition of climatic shadowiness where visibility of article is decreased beneath 1 Km. In the event that visibility dips under 40 meters, mist is qualified as being "thick". A visibility between 40 meters and 200 meters compares to a thick haze situation.

For street security applications, the visibility scope of intrigue is somewhere in the range of 0 and 400 meters. The glowing transition exuding from obvious light (400 nm $\leq \lambda \leq$700 nm) gets dispersed every which way when it hits a water bed and assimilation is frequently immaterial for this situation. This dispersing can seriously debilitate drivers' profundity discernment and fringe vision. The lessening of obvious light is described by the termination coefficient k (m-1) which is a factor of the beads measure and concentration. The estimation of this coefficient has been the premise of numerous visibility run estimation strategies. Light proliferation through haze based on Koshmieder luminance lessening law,Duntley[11] proposed the constriction law of air differentiates under uniform illuminance which expresses that an item with inborn complexity C0 without wanting to be seen at a separation d with an evident difference C given by:

$$C = C_0 e^{-kd} \quad (1)$$

(1) The above articulation has been utilized as a reason for characterizing the "meteorological visibility remove" $d_{visibility}$ as the best flat separation at which a dark article (C_0=1) of a moderate measurement can be seen seemingly within easy reach amid daytime with a differentiation limit ε=5% , as prescribed by the International Commission of Illumination(IEC8): (2)

$$d_{visibility} = -\frac{1}{k}\ln(0.05) \cong \frac{3}{k} \quad (2)$$

The above basic articulation recommends that, from the termination coefficient k of the encompassing environment, one can determine the apparent visual scope of a dark item at daytime.

III VISIBILITY SEPARATE ESTIMATION TECHNIQUES AND ARRANGEMENTS

Estimation of range can be an overwhelming assignment given the non-uniform nature of the physical environment and the interlacing components impacting visibility which incorporate power of encompassing light, physical properties of articles, light dissipate and ingestion among numerous others. Different visibility separate estimation approaches for transportation frameworks have been proposed over the previous years. These methodologies vary in different perspectives (daytime versus evening time, mist identification or potentially visibility estimation, optical versus picture sensors, fixed cameras versus locally available cameras, video-based versus picture based; calculation utilized for picture handling and separation estimation, and so forth).

LiDARs have been utilized to assess visibility under foggy climate conditions by breaking down the flag backscattered by haze droplets[12]. As revealed by Colomb[13], this methodology, in any case, requires calibrating of the LiDAR's capacity to adjust to the elimination coefficient k. There has been a developing enthusiasm amid the previous couple of years in utilizing fixed cameras (set on the roadway) or (and to a lesser degree) locally available cameras to assess visibility remove, as these gadgets are moderately shabby and are as of now sent for traffic observing and reconnaissance on major expressways.

Camera-based methodologies can be characterized into three primary classes: The principal (type-I) approach plans to quantify the separation to the uttermost dark focus in the picture while as yet showing a differentiation more prominent than ε=5% according to the IEC recommendation[14,15]. This includes looking for focuses or districts of enthusiasm by applying thresholding and division strategies to find indicated targets, for example, path markings[16], street signs[17], street limits, or the crossing point between street surface and the sky[12]. The fundamental downside of this methodology is that it requires exact geometric adjustment of the camera and it depends on the nearness of reference objects with high differences in the scene.

The second (type II) approach depends on processing the scene differentiation and afterward playing out a direct relapse between this complexity and the visual range that is figured with the guide of extra reference sensors[13]. This methodology does not require camera adjustment or the nearness of reference objects. Nonetheless, it involves a learning stage that requires the use of extra meteorological sensors.

The third (type III) approach utilizes a worldwide descriptor vector which is registered in general picture, independent of its substance. This methodology does not require edge location or learning of the separation to different reference targets. The worldwide descriptor vector reflects data about the worldwide picture differentiation and utilizations highlights dependent on the inclination whole or the Fourier coefficients sum[15] as these are invariant to enlightenment changes. Our proposed neural system approach falls inside this class.

IV THE PROPOSED NEURAL SYSTEM APPROACH

Our methodology comprises of evaluating visibility extend through an administered preparing connected to marked models that are portrayed by worldwide instead of neighborhood highlights. Our classifier is a three-layer neural system prepared with a back-spread calculation. The principal input layer is the component vector picture descriptor. The concealed layer comprises of a lot of completely interconnected computational hubs whose number is resolved exactly.

The yield layer is a vector whose measure is equivalent to number of classes, which for our situation compares to various visibility ranges. For the worldwide element descriptor, we have settled on a Fourier Transform approach which is viewed as a standout amongst the most effective picture change techniques[18] and it catches the power range of the picture. As a result of the high dimensionality of the Fourier change extent descriptor, we have brought a dimensionality decrease through Principal Component Analysis (PCA). Notwithstanding the Fourier extent descriptor, we have likewise utilized Shannon entropy as a second descriptor that portrays a picture surface by investigating its dark dimension dissemination as per the accompanying articulation: (3) where Pi is the likelihood that the contrast between 2 nearby pixels is equivalent to I. The last total descriptor is a mix of the mean squared Fourier change vector decreased by the PCA and the picture entropy.

Fig. 1. Longest Sensors which are used in front and Rear of Vehicle.

$$E = \sum_{i=1}^{n} P_i \, log_2(P_i) \qquad (3)$$

V TRIAL ASSESSMENT AND RESULTS

In this investigation, we have considered six classes of visibility go (< 60m, 60m - 100m, 100m - 150m, 150m - 200m, 200m - 250m, and ≥ 250m). We have utilized the element vectors separated from the pictures to gain proficiency with the required visibility classes. Tentatively, we kept up just the initial 100 eigenvectors since they speak to close 99% of the total percent of change. Figure 2 delineates the general engineering of the neural system where I1-I20 speak to the components of the information descriptor vector, H1-H12 are the shrouded layer hubs and the yields compare to the visibility ranges.

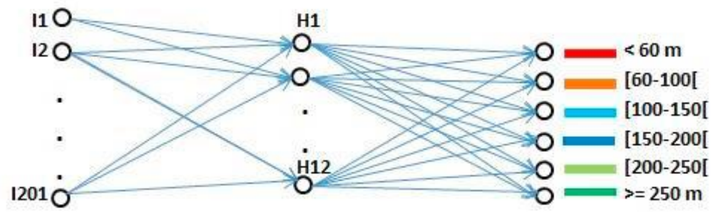

Fig.2. Neural system layers

To assess our proposed methodology, we have utilized the FROSI (Foggy Road Sign Images) database[19]. This database contains an arrangement of 400 manufactured pictures with 1000 street signs put at different extents. For each picture, a lot of 7 kinds of uniform mist thickness are accessible with visibility separations going from 50m (substantial haze) to 400m (slight haze), as appeared in the illustrative precedent in figure 3.

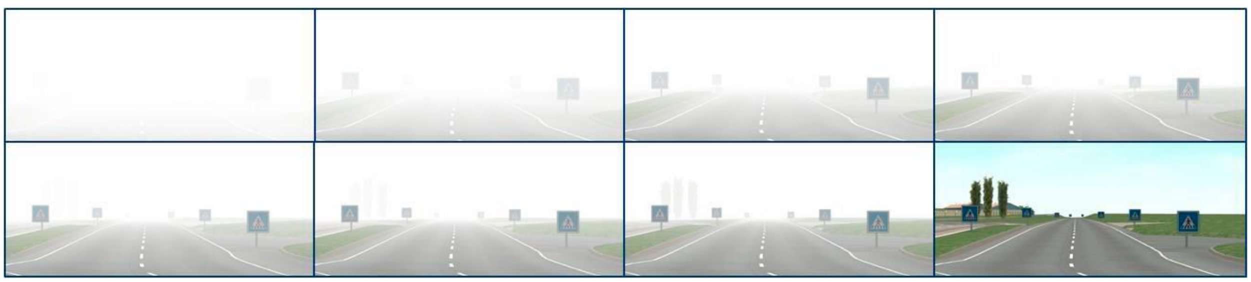

Fig. 3. Test of pictures from the FROSI database

We have likewise looked at the exactness of our proposed arrangement with that dependent on sort I approach. For our situation, no following/recognition steps were required as traffic sign positions were known from the earlier. For sort I approach, we have embraced Michelson differentiate recipe $C = (I\text{max} - I\text{min})/(I\text{max} + I\text{min})$, where Imax and Imin indicate the greatest and least pixel power, individually. For the neural system preparing stage, we have utilized 336 pictures under various visibility ranges. The weighted neural system was along these lines tried utilizing an alternate arrangement of 336 pictures under different haze thickness conditions. Our outcomes are abridged in the perplexity lattice portrayed in figure 4(a). In general, a 90.2% effective arrangement rate was accomplished, contrasted with a 65% achievement rate acquired through sort I approach. As appeared in figure 5(b), our methodology gives better outcomes under all visibility classes. We see that the 6th class has the base likelihood of identification (83%) because of disarray with extents somewhere in the range of 150 and 250 meters.

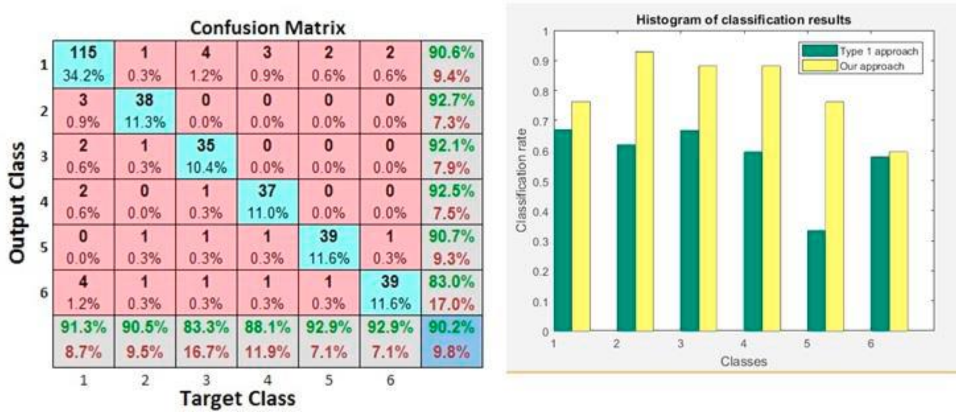

Fig. 4 (a) Confusion matrix; (b) Comparison of results

VI CONCLUSION

Road traffic accident severity keeps on changing over time and increase endlessly. The changing and increasing road traffic accident severity leads to the issues of not understanding the accident behavior, factors influencing the traffic accident severity. In this contribution, we have presented a neural network approach to estimate visibility range under foggy weather conditions. First, here we only utilized the traffic accident data itself for prediction. However, other related data, such as traffic flow, human mobility, road characteristic and special events, maybe significant to traffic accident risk prediction as well. Second, our prediction results are coarse-grained, and cannot provide road level accident risk prediction. Our solution requires a single camera which can be fixed on the roadway side or placed onboard a vehicle or high speed sensors. Our approach provided visibility range estimates that are close the expected values for a wide range of fog density scenarios. A key advantage of the proposed approach is that it is inherently generic and does not require special camera calibration or a prior knowledge of distances in the depth map. Our proposed algorithm can be implemented on existing camera-based traffic monitoring systems, which can serve as a driving aid to warn motorists and request them to adapt their speeds according to the estimated visibility distance. We are currently working on further refining our approach and comparing it with additional methods identified in our literature review.

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