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An Intelligent Road Traffic and Accident Advisory System

UMEJURU DANIEL[1], ANTHONY VIVIAN ONYIYECHI[2]
[1]*Department of Computer Science, Abia State University, Uturu, Nigeria*
[2]*Department of Computer Science, University of Port Harcourt, Choba, Nigeria*

Abstract- As commuters continue to make movements through road transportation daily, many lives are feared to be lost owing to poor road condition and lack of proper road maintenance. This has made road and safety specialist, think deeply on how to proffer a long and lasting solution to this menace using a modernized and smarter approach. This research proposes an intelligent advisory system against road accidents. It proffers trip advisory using some key parameters such as origin of movement, destination and time of day. The advisory results for a trip from Abia to Rivers State in Nigeria as seen in study, depicts key terms such as risks levels recorded as medium, score 0.42%, and common reasons for its advice such as bad road with 36 records and over speed with 65 records. Data visualization was used to properly show level of accidents by state and also accident by time of day while the conjestion level confusion matrix, fore tells when a particular desired road is conjested in other to take alternatve routes whilst showing true and predicted values as well. The diagnostic tools employed for the models' performance evaluation are Accuracy 0.64%, Precision 0.65% and Recall 0.33% respectively. Summarily, this research has successfully developed an intelligent road advisory system which proffers trip advisory based on certain parameters as explained in other for a properly guided journey of commuters as they use the road daily to avoid reoccurring mishaps.

Keywords: Intelligent, Advisory, System, Risks, Speed

I. INTRODUCTION

The intricate interplay involving one or more of the four main factors—person, vehicle, road, and environment in order to effectively determine the severity of traffic accidents; it has been determined that the human element is the most significant but also the most difficult to modify [6]. Accidents on the roads cause substantial losses for both the concerned parties and the nation in terms of infrastructural damage, lost production, and payouts from road accident funds [1]. Achieving global environmental objectives and making traffic safety and accident prevention a priority in the management of transportation is contingent upon reducing or preventing these numerous losses [14]. Every road tragedy result in the collection of an accident report, which includes various accident characteristics and can be utilized to look into the incident's potential cause at that specific segment of the road [5].

Nevertheless, it comes to the accessibility of trustworthy accident data, the majority of developing and underdeveloped nations are falling beyond the rest of the globe [12, 13]. Stretches of road with a high frequency of accidents can also be identified from collision reports, and these areas are then the topic of an accident study that may entail the expert reconstruction of accident scenes [3]. Replicating the real-world behaviors of the drivers and the technical functioning of the vehicle that caused the accident can be costly and difficult when reconstructing a scene from an accident. Therefore, for an existing road or a newly constructed road network, the utilization of accident traffic data and analytical tools could be helpful in anticipating and preventing a future traffic accident [2].

II. RELATED WORK

Very few accident predictive models (APMs) are utilized for predicting accidents on parts of metropolitan main roads. Studies that are now available show that a large variety of ML techniques are employed to evaluate the safety of different road features, including the existence of a median, two-way left turns, speed restrictions, the quantity of points of intersection, and pedestrian density [7]. It is difficult some times to identify which geometric property might account for the accidents that occur

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along urban road segments. These models have numerous explanatory variables as proposed by [4].

$$E\{k\} = \alpha LYF^{(\beta_1)} e^{([x^{(\beta, x_i)}])} \qquad 2.1$$

Where E{k} is the expected number of road accidents in a specified period of time L is the length of road segment, Y is the number of years, F is the traffic flow on road segments, xi is the series of independent features for the ranging j=2 to m and α, β1, βi are the coefficients variables to be estimated which I range from 2 to m. A model was developed by [10] for predicting property loss and injuries from traffic accidents. Eight explanatory variables total, including numerous dummy variables (such as 1 or O), made up the best-fitting model that was produced.

They employed two distinct models: one for intersections and one for mid-block sections—instead of utilizing a single model to forecast accidents for the full road segment. They had a model form that resembled equation 2.1. [8] Proposed isolating incidents that transpired among junctions from those that occurred at intersections. They suggested two APMs: a single for mid-block segments and another for intersections. The form of the accident prediction model for mid-block road segments was as follows:

$$E\{R\} = \alpha e^{(x_i^{(\beta_i . x_i)})} \qquad 2.2$$

Were

E{R}is the expected road accident rate measured in 108 vkms

Xi is a series of independent variable and i variable range from 1 to 5

X1 denotes residential development when its equal to 1 and zero (0) as otherwise

X2 is the flush median when its equal to zero (0)

X3 =1 is the solid median and x3=0 otherwise

X4 =1 is for 50 kilometer per hour, and zero otherwise

X5 is the number of intersections per kilometer

α, βi is the coefficients to be estimated with I ranging from 1 to 5.

The intersection length and being exposed are both included in the formula provided in equation 2.2. The creation of APMs for highway route segments with minor intersections when traffic counts for intermediate approaches are unavailable [11]. The system they created was designed for isolated highways, and it continues to remain in use today because conventional methods are unable to predict accidents on certain road sections where traffic counts are not always conducted at all junctions along a highway corridor [9]. The following forms appeared in their proposed road accident prediction model.

$$E\{K\} = \alpha L^{\beta_1} F^{\beta_2} e^{(\beta_3 N)} \text{ and } E\{K\} = \alpha L^{\beta_1} F^{\beta_2} \qquad 2.3$$

Where E{k} is the total number of expected road accidents on intersection per unit of time

L = Length of road intersection, F= the traffic flow on the road segment

α, β1, β2, β3 are the coefficients to be estimated

Equation 2.3 has a significant attribute pertaining to the link between accidents and sectional length. It is frequently believed that the number of accidents increases with the length of an automobile section. This association might not hold true in all situations. For example, equation 2.3 demonstrates the absence of the connection by allowing the variable L to be different from 1.

III. PROPOSED SYSTEM WORKFLOW

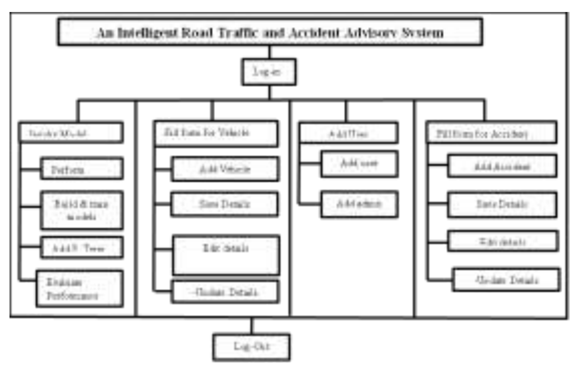

Figure 3.1: Proposed System Workflow

The proposed system provides an easily understandable overview of the key concepts and principles of a likened architecture. The system is utilized as an abstract representation of useful data to help a user communicate with the system via human computer interaction (HCI). Every user must have a unique background and experience level. The purpose is to facilitate communication with the new model. It facilitates data exchange by being utilized in the design of models in the databases and information systems. It facilitates effective communication between user and system with varying backgrounds and degrees of experience.

This will help identify stake holder and available resources. The diagram above illustrates the link between the proposed system workflow features, and demonstrates dependence with respect to various degrees of abstraction.

IV. RESULTS

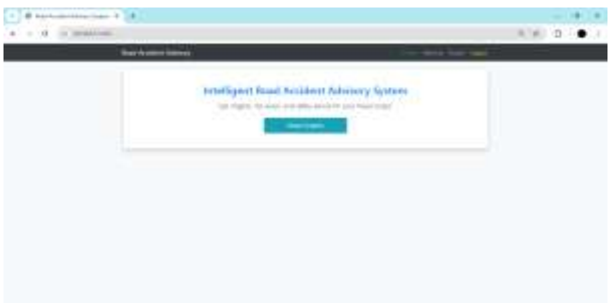

Fig 4.1: Home Page

Fig 4.1 shows the home page of the intelligent advisory system

Fig 4.2: Trip Advisory Page

Fig 4.2 shows the trip advisory page using parameters such as origin of journey, destination desired and time of day in other for the system to properly advise user.

Fig 4.3: Advisory Result Page

Fig 4.3 shows the advisory result recording risk level as medium, score as 0.42 and an advice for a normal speed range considering bad road of 36 records and overspeed of 65 records on desired road.

Fig 4.4: Data Visualization Page

Fig 4.4 shows the data visualization of accidents by states by origin, with Oyo state having the highest case of recorded accidents, and also accident by time and day showing that more accident occurs in the afternoon due to busy nature of the day and high road usage.

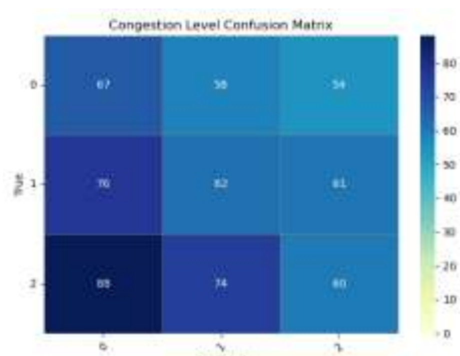

Fig 4.5: Confusion Matrix for Congestion Level

Fig 4.5 shows the conjestion level confusion matrix fore tells when a particular desired road is conjested

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in other to take alternatve routes too showing true and predicted values as well

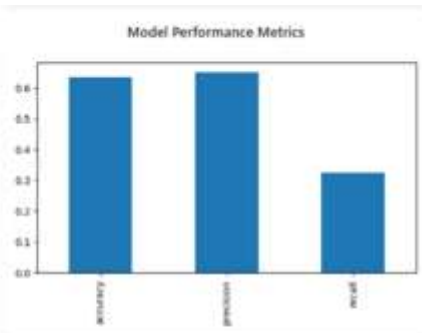

Fig 4.6: Model Performance Metrics Page

Fig 4.6 shows the models performance using metric tools such as accuracy 0.64%, precision 0.65% and recall 0.33% respectively.

CONCLUSION

Owing to poor road condition and lack of proper road maintenance which threatens lives and doesn't guarantee safety of commuters daily, this research successfully developed an intelligent road traffic and accident advisory system. The system proffers trip advisory using key parameters such as origin of movement, destination and time of day. The result proved efficient showing key terms such as risks levels recorded as medium, score 0.42% and common causes of its advice such as bad road with 36 records and over speed with 65 records. The congestion confusion matrix was also used to fore tell when a desired road by user is congested by traffic and further suggests a better route to take whilst showing true and predicted values as well.

The model has been tested and performed efficiently well and can be used to get advice on future trips on road with bad conditions and lack of maintenance.

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