AN EFFICIENT UBIQUITOUS-BASED ROAD ACCIDENT DETECTION FRAMEWORK USING ARTIFICIAL NEURAL NETWORK AND HAVERSINE ALGORITHM

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ABSTRACT
Road accidents are a common feature of the Nigerian road transport system. The increase to the road accidents cases are as a result of bad roads, weather and many other environmental situations. Many deaths occur not just because of the occurrence of the accidents but because of the delay in arrival of the rescue teams. In this work, we proposed a framework for early detection of road accidents which utilized the ubiquitous nature of the smart phone, Artificial Neural Networks (ANN) and haversine algorithm. The ANN used an input layer made of four nodes and a single middle layer made of six nodes together with the backward propagation algorithm to detect the occurrence of an accident. Once an accident was detected the haversine algorithm was used in providing the location as well as the shortest path to the location of the accident. Experimental results with the framework showed that the framework was not only able to detect the occurrence of an accident but also indicated the location and the shortest path the rescue team can take to the location of the accident. The accident detection framework was implemented using java programming language. Six experiments were conducted to show the ability of the framework to meet its objectives. The framework was able to detect the occurrence of an accident with high accuracy and suggest the shortest path to accident scene.

Keywords: Haversine Algorithm, Ubiquitous Sensor Network, Mobile Clients, Data Acquisition

INTRODUCTION
The increase in incidence of road accident every day in the world especially in developing countries like Nigeria is still a thing of concern despite the progress made over time in this area of research. Due to growth in urbanization and increase in the number of vehicles, road traffic accidents have been on the rise on an alarming rate with high number of deaths and injury cases. National Bureau of Statistics (NBS) (2018) reported that 2,242 road accidents have occurred in the first Quarter of 2018 (Q1 2018) in Nigeria and a total number of 1,292 Nigerians got killed.

This makes road accidents one of the most important problems faced by the Nigerian society. Overall road collisions are the second leading cause of death for people between the ages of 5 and 29 and third leading cause for people between 30 and 44 (Hamid and Alwan, 2015). It has been observed that when most accidents occur, victims are not given the required help on time due to lack of early detection system for reporting of accident scenarios. This paper looks at a new dimension to solving the problem at hand using ubiquitous computing device (i.e the smartphone), Artificial Neural Network techniques as the detection algorithm and the Haversine algorithm for finding the closet response team to the accident scene or location. The goal of this work is to use Artificial Neural Network for detection of the occurrence of road accident, the haversine algorithm to locate the shortest path to the accident scene and the input parameters of the ubiquitous device (smartphone) to develop a framework for road accident detection for efficient and prompt reporting of accident scenarios to appropriate authorities.

RELATED LITERATURE
Road safety is one of the serious challenges currently facing humanity especially in the developing world. Thus, in order to address this issue, we have explored existing research work on tools, technologies and methods used in detection systems, and various techniques used in accident detection system and as well investigated related works along the lines of ubiquitous computing in building a framework for accident detection as discussed below.

Assem (2013) defined ubiquitous computing as a post-desktop model of human-computer interaction in which information processing has been thoroughly integrated into everyday objects and activities. Similarly (Weiser, 1991) described ubiquitous computing as technologies that weave themselves into the fabric of everyday life until they are indistinguishable from it.

Khali et. al. (2018) used two ultrasonic sensors to detect an accident occurrence. The ultrasonic sensor was used to determine the distance between objects by sending and receiving reflected sound waves. The time between wave
generation and reflection was used to calculate the distance between objects. One ultrasonic sensor module is placed on the wind screen or the front side of the roof of the car, to measure the distance from the wind screen or the roof to the front bumper of the car. The distance was the first threshold distance that was pre-defined on the system. Another ultrasonic sensor module was placed on the back side of the roof of the car and again we measure the distance from the back roof to the back bumper of the car. This distance was the second threshold distance that was pre-defined on second system. When a vehicle or any object is away from the bumpers of a car, the systems will not react because this distance is always greater than our threshold distances. Whenever any vehicle or any obstacle will collide with the car from front side or back side, and within the range of pre-set threshold distance, then respective system immediately turns on and determines the location of car using the GPS module. Then it will send information using the GSM module to the emergency department. Through this process the system detects an accident and communicate the information to the rescue team.

Urban fire outbreak has remained a challenge in urban settlement. Agaji and Shagbum (2016) implemented a mechanism for fire detection using Artificial Neural Networks (ANN) with backpropagation method to detect the occurrence of urban fires. Their systems smoke density, room temperature and cooking gas concentration as inputs and was implemented using Java programming language.

Soliman et al. (2010), combined the use of Wireless Sensor Network and Artificial Neural Networks (ANNs) to build a "smart forest-fire early detection sensory system" (SFFEDSS). In their research data (e.g., temperature, light, and smoke) was collected from the field via a Sensor Network (SN) cell of ten sensors. All readings were transmitted to an already trained ANN at a base station in order to detect fire incidence.

Yoo et al (2008) presented an Intelligent traffic control system (INTRAC) that utilized Ubiquitous sensor network (USN), and RFID for accident detection and propagation of accident information to neighboring vehicles. The system comprises of seven components, namely: Intelligent Transportation System (ITS) Server, ITS Client, Micro Control Unit(MCU), Zigbee, RFID Reader, RFID Application Level Event (ALE) Server, and RFID Client. The ITS client is designed to help administrators manage their system at ease, with the responsibility of processing messages from the ITS server and displaying traffic and atmospheric information on the screen. Assuming any message is considered as a car accident, it notifies a police station or a fire station of an accident, providing emergency medical services and technical rescue for drivers.

Ozbayoglu et al. (2017) proposed a real-time autonomous accident-detection system based on computational intelligence techniques. The researchers employed the use of big data processing methodologies, on 2015 traffic flow data collected from various sensor locations of Istanbul City. The results indicated that even though the number of false alarms dominates the real accident cases, the system can still provide useful information that can be used for status verification and early reaction to possible accidents.

Zhang et al. (2017) proposed a deep learning approach for detecting traffic accident that utilized social media data (twitter), using 3 million tweet contents related to traffic accidents in two cities within a period of one year. The results show that social media data might be noisy and even unreliable. Therefore, social media in accident detection can function as a secondary source rather than a replacement to the traditional method.

Khan et al. (2018) proposed the use of the pre-embedded capabilities of the smart phone for accident detection for the two wheelers on the road. The framework is designed to keep check of various and external road conditions that could be fatal to the driver. With real time analysis and alerts of these factors, the researcher attempts to increase a driver’s overall awareness in order to maximize safety, using the embedded features of the smart phone such as the three-axis accelerometer and a GPS tracking system. Their work consisted of a smart phone application, ambulance unit, and cloud server used to detect accidents in order to provide an ambulance to scene using the Accelerometer and GPS with the core aim of minimizing the delay involved while providing ambulance support.

WreckWatch is a prototype smartphone-based client/server application developed by White et al. (2011), that implements a mechanism to provide accident detection and notification by using the embedded smartphone sensors and communication interfaces. The WreckWatch presents a formal model for accident detection that combines sensors and context data, this system automatically detects accidents traffic accidents using accelerometers and acoustic data, and immediately notifies a central emergency dispatch server after an accident, and provide situational awareness through photographs, GPS coordinates, VOIP communication channels, and accident data recording. Although the literatures reviewed showed success in detecting accident occurrences, there is need to improve the detection phase of the accident detection system as suggested by Hamid et al (2015).

All the works reviewed could suggest location of accident without suggesting any path to the location.

**METHODOLOGY**

The proposed framework is based solely on an Artificial Neural Network (ANN) approach using backpropagation algorithm for road accident detection, and Haversine algorithm for finding the closest response team to the accident location. The ANN was used because of its ability to be implemented in parallel architectures thereby reducing processing time compared to the other kind of approaches used by other researchers and its ability to solve nonlinear and complex problems such as (damage detection, fire detection) with high degree of accuracy, and the
Haversine was also used because of its high-level accuracy in finding paths on the Euclidian space.

The proposed framework consists of three phases. These are data acquisition, detection and notification phases. The data acquisition provides the resources for the detection phase. The phase consists of a dataset with readings from smartphone accelerometer sensor which continuously measures the acceleration information recorded in G-force, Speedometer which specify the speed the vehicle is moving, GPS receiver which synchs the longitude and latitude of the vehicle with the framework in order for the Haversine algorithm to determine the shortest path for the rescue team. The phase also has smartphone microphone which indicates high decibel acoustic events such as sound of airbag noise, clock which measures the time elapsed, which is the measure of the maximum time the vehicle was travelling from the last location where the speed has reduced below the speed threshold of 24km/h. The Data in the dataset was randomly generated.

The detection phase is made up of the ANN whose input layer is made up of smartphone accelerometer sensor, GPS receiver, clock, and built-in microphone in order to determine the occurrence of road accident. The ANN comprised a multilayer perceptron neural network (MLPNN) using backpropagation method with three layers of units (i.e. input layer, hidden layer and Output layer). The ANN architecture for the framework is shown as Fig.1.

\[
d = R \times c \\\n\]

Where R is the mean earth’s radius given by R=6371KM, d is the optimal path to the scene of the accident and is defined by

\[
c = 2 \times \arctan(\sqrt{a}, \sqrt{(1-a)}) \\
\]

and a is defined by

\[
a = \sin^2\left(\frac{\Delta \varphi}{2}\right) + \cos\varphi_1 \times \cos\varphi_2 \times \sin^2\left(\frac{\Delta \lambda}{2}\right) \\
\]

where \( \varphi \) is the latitude and \( \lambda \) is the longitude.

**Design of the framework**

The architecture of the proposed framework is as shown in fig 2. The inputs are synched to the framework by a mobile client resident on the smartphone of the user, the artificial neural network processes the data and the result is provided through a notification to the response team. The architecture reflects the three phases of the framework.
The framework’s state diagram is shown in fig3. State diagram is chosen above other design artifact because of the changing states of a moving vehicle on a road. A vehicle is in safe state if there is no accident ie the mobile client generates input for the framework that does not guarantee an accident. A vehicle can also enter an accident state ie If the computation on the inputs results to a change of state from a safe state to an accident state. Once in the accident state the framework acquires the location of the location and moves into the notification state.

**IMPLEMENTATION, RESULTS AND DISCUSSION**

The data used for the simulation of our framework were randomly generated however these data had same resemblance as the attributes of the inputs. 500 datasets were generated of which 400 datasets were used for training and 100 datasets were used for testing the network. The work was implemented using java programming language and MYSQL was used for the design of the database for storing details of the emergency team and a log of the detections made by the framework.
Experimentation
Six experiments were carried out using the randomly generated data sets shown in table 1. The randomly generated datasets were normalized as shown in table 2.

Table 1: Unnormalized dataset used in the experiments

<table>
<thead>
<tr>
<th>S/N</th>
<th>Aceler(G)</th>
<th>Speed(Km/h)</th>
<th>AirbagNoise(db)</th>
<th>ElapsedTime(sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7</td>
<td>177</td>
<td>90</td>
<td>18</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>39</td>
<td>151</td>
<td>12</td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>268</td>
<td>150</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>15</td>
<td>35</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>3</td>
<td>152</td>
<td>8</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>7</td>
<td>47</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 1 shows six sets of unnormalized inputs were used in the experiment.

Table 2: Normalized dataset used in the experiments

<table>
<thead>
<tr>
<th>S/N</th>
<th>Aceler(G)</th>
<th>Speed(Km/h)</th>
<th>AirbagNoise(db)</th>
<th>ElapsedTime(sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7000</td>
<td>0.5900</td>
<td>0.53333</td>
<td>0.5862</td>
</tr>
<tr>
<td>2</td>
<td>1.0000</td>
<td>0.1300</td>
<td>0.94000</td>
<td>0.3793</td>
</tr>
<tr>
<td>3</td>
<td>0.9000</td>
<td>0.8933</td>
<td>0.93333</td>
<td>0.0690</td>
</tr>
<tr>
<td>4</td>
<td>0.2000</td>
<td>0.0500</td>
<td>0.16667</td>
<td>0.0690</td>
</tr>
<tr>
<td>5</td>
<td>0.1000</td>
<td>0.0100</td>
<td>0.94667</td>
<td>0.2414</td>
</tr>
<tr>
<td>6</td>
<td>0.1000</td>
<td>0.0233</td>
<td>0.24667</td>
<td>0.3793</td>
</tr>
</tbody>
</table>

RESULTS AND DISCUSSIONS
The results of the framework are as shown in table 3. In table 3 the value 0.5 and above in the DetectionValue column shows the occurrence of an accident while a value of less than 0.5 indicates otherwise. In the experimental results shown in table 3 three accident scenarios where detected and three safe state were also detected. The accidents were detected in serial numbers 1, 2 and 3 because the DetectionValue in each of the cases was greater or equal to 0.5. The corresponding locations, in terms of latitude and longitude, where the accidents took place were list under LocationOfAccident column of the table. Safe states where found in serial numbers 4, 5 and 6 because the DetectionValue in each of the cases was less than 0.5. In the safe states, because no accident occurred no location was outputted.

Table 3: Results of the Experiments

<table>
<thead>
<tr>
<th>S/N</th>
<th>DetectionValue</th>
<th>LocationOfAccident</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.999996997419</td>
<td>7°41'06.4&quot;N, 8°32'11.2&quot;E</td>
</tr>
<tr>
<td>2</td>
<td>0.99999997334</td>
<td>7°42'36.2&quot;N, 8°37'05.7&quot;E</td>
</tr>
<tr>
<td>3</td>
<td>0.99999300911</td>
<td>7°44'15.2&quot;N, 8°30'20.2&quot;E</td>
</tr>
<tr>
<td>4</td>
<td>5.74378047E-6</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2.130515624E-6</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>7.248425254E-6</td>
<td></td>
</tr>
</tbody>
</table>

When an accident is detected the corresponding location is sent to the rescue teams. Fig 4 shows a sample notification sent to the rescue team. The sample notification is sent to the mobile number of the rescue team and it specifies the location of the accident in terms of longitude and latitude.
Fig 4: Sample Notification to rescue team

Fig 4 shows the sample notification sent to rescue team alerting them of the occurrence of an accident. It spells out the location of the accident in terms of the latitude and longitude of the location. The location of latitude 7.685111N, and longitude 8.536444E was detected as the location where the accident occurred. The Haversine algorithm then specify the shortest direction of the accident location. The google API was used to show the location on map. The shortest path to the location of the accident is shown in fig 5. The shortest path to the accident scene was highlighted in blue.
CONCLUSION

This paper has brought a new dimension to road accident detection and reporting problem. The results of the work were compared to results from White et al. (2011), Hamid et al. (2015) and Khan et al. (2018) and it was found that the result exhibited high level of accuracy in accident detection as the other works however the work provided the shortest path to the accident scene which was lacking in the other works. The work is recommended for use by all agencies involved in rescuing road accident victims.

REFERENCES


