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# A new approach for varied speed weigh-in-motion vehicle based on smartphone inertial sensors

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## Article Info

## ABSTRACT

Dynamic vehicle weight measuring, weigh-in-motion (WIM), is an important metric that can reflect significantly vehicle driving behaviour and in turn, it will affect both safety and traffic status. Several accurate WIM systems are developed and implemented successfully. These systems are using under road weighing sensor which are costly to implement. Moreover, it is costly and not very practical to embed a continuous weighing system in used cars. In this work, a low-cost varied-speed weigh-in-motion approach was suggested to continuously measuring vehicle load based on the response of smartphone sensors which is a reflection of vehicle dynamics. This approach can apply to any moving vehicle at any driving speed without the need for extra added hardware which makes it very applicable because smartphone is widely used device. The approach was tested through a six-trips experiment. Three capacities of load had been designed in this approach to be classified using a neural network classifier. The classification performance metrics are calculated and show an accuracy of 91.2%. This accuracy level is within error limits of existing WIM systems especially for high speed and proved the success of the suggested approach.
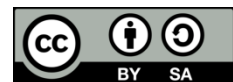
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## 1.   INTRODUCTION

All user and road safety, pavement design, bridge design and other transportation issues depend mainly on dynamic vehicle weight or what is called weigh-in-motion (WIM) [1]–[3]. Numerous methods of dynamic vehicle weighing scales are developed to fit the requirements of this need. However, these methods used different types of sensors and load cells with data loggers to measure and record the weighing data.

Recently, smartphone ubiquity and development of its hardware, built-in sensors, and software help to involve this device in most life applications. The use of smartphone sensors in these applications offers an easy and cost-effective solution. Different areas of transportation and vehicle safety utilized smartphone sensors rather than traditional systems as detailed below:

A different area of smartphone-aided application is physical activity and health monitoring. Although it is not related to transportation but smartphone sensors are widely used in this area. In 2013, another researchers studied the utilization of smartphone accelerometer, gyroscope, and magnetometer in recognizing the physical activity. They presented the evaluation of three sensors in four body situations positions by using seven classifiers while identifying six physical activities [4]. Hernandez *et al*. have developed a method that benefits from accelerometer data for extracting breathing and heart rate [5]. Another researcher used smartphone texting activity to identify operator fatigue [6]. In 2021, G. Ali and her team proposed a recognition

system for human physical activity. The system is based on data extracted from smartphone sensors i.e. gyroscope, accelerometer, and gravity sensor. The results presented high accuracy in recognition of all six activities especially with related to running, walking, sitting, and standing [7].

Many research papers were studying vehicle accidents and road conditions using smartphone sensors. In 2013, Roberto G. and his team introduced good results concerning utilizing smartphone in crash detection of vehicles. The presented model has been examined for early detection of traffic accidents [8]. While Adnan Bin Faiz et al developed an application based on Android to detect an accident and notify the nearest health care center and police station by emergency alert message. They utilize an external pressure sensor tends to extract the body outward force of the vehicle. Global positioning system (GPS) and accelerometer sensors have been used in the application, so they became capable to reduce the rate of false alarm by measuring speed and change of tilt angle respectively [9]. In 2017, another researchers presented an intelligent system for detecting road surface conditions. They used smart mobile relying on crowdsourcing and sensing technique. The sensors used in smartphone such as GPS and accelerometer have been utilized for monitoring several road conditions [10]. Moreover, different research areas related to use smartphone in vehicle and transportation areas such as internet of vehicles (IoV) [11], road condition [12], accident type classification [13].

Another field of using smartphone sensors in transportation area is driving behaviour. In 2016, Li *et al.* [14] present a driving behaviour detection method using low accuracy accelerometers and gyroscopes. The algorithms have been proved experimentally [14]. And in 2019, Sasidhar and Upasini developed a method uses a smartphone accelerometer for detecting and identifying abnormal driving behaviour such as lane changing, weaving, and sudden braking [15]. Recently, Rishu Chhabra and his colleagues designed and implemented an accelerometer to detect any unexpected changes in acceleration, sharp turns, and braking using gyroscope. The method categorized the driver as an aggressive or nonaggressive driver according to the observed pattern [16]. And in 2019, Papadimitriou *et al.* [17] explored driver behaviour using smartphone sensors. They suggested using mobile phone while driving for more accuracy [17]. Although of many research papers that had been presented in on-road weighing area [2], [18], [19], to our best knowledge there were not trials of using smartphone sensors to handle this task. In this work, a new approach is proposed to classify on-road truck weight into three classes using smartphone magnetometer and inertial (accelerometer and gyroscope) sensors. This approach is very cost-effective and can be implemented easily to any vehicle without the need for extra hardware to be installed by professional workers.

## 2. BACKGROUND

Different approaches, methods and systems had been proposed in research papers to investigate the accuracy of these proposals and their ability to keep this accuracy in real road environments. It is known that static weighing is more accurate than dynamic weighing. However, still, dynamic weighing is preferable because of its ability to ensure traffic flow and reduce the need for stopping at the entrance of static weighing platforms. In the next subsections, several topics related to our work are detailed with its background theory.

### 2.1. WIM

Weigh-in-motion systems are used to measure weight of traveling vehicle at normal or reduces speed. Collected data from WIM system is very useful for vehicle suspension system, pavement and traffic control and other applications. WIM systems can be classified into two major classes: i) low-speed WIM (LS-WIM) and ii) high-speed WIM (HS-WIM). This classification is come up based on vehicle speed. The system is counted as LS-WIM if the measuring speed is up to 15 km/hr, while it will be under HS-WIM class if it crosses the 15km/hr, threshold [20]. The weight sensors may be embedded in roads, bridges or installed in vehicles (on-board WIM). LS-WIM can be implemented using road sensors while HS-WIM can be implemented using all three systems as illustrated in Figure 1 [21], [22].

Accuracy, cost, traffic management, availability and frequency of calibration are main issues need to be investigated to improve the use of WIM systems in real environments. The accuracy of WIM existing systems is around 5-15% depending on vehicle speed and number of sensors and other parameters [21]–[23]. However, increasing number of sensors makes the system costly and sophisticated and rise the need for a more frequent calibration process. The proposed approach is suggested to in keep the existing accuracy and, at the same time, improve the cost and ease of use with increasing frequency of calibration.

### 2.2. Vehicular dynamics

Vehicle movement follows mainly Newton's second low which describe the relation between mass (*m*), acceleration (*a*) and vehicle net forces (*F*) as shown in (1):
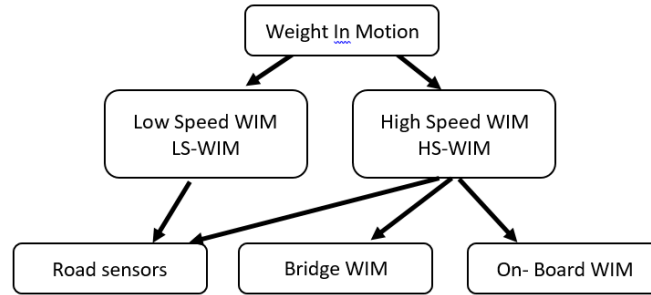
$$F_{net}=ma \tag{1}$$

Figure 1. Weigh-in-motion classes

where the net forces ($F_{net}$) is the resultant of traction force and resistance forces [24]. Starting from Newton's second low more detailed formula is derived from [20]:

$$F = m \times a + m \times g \times \sin\theta + R \tag{2}$$

where $F$ is the combustion engine driving force, $m$ is the mass of the derived vehicle, $a$ is the vehicle acceleration, $g$ is the gravitational acceleration, $\theta$ is the slope angle of the driving road and $R$ is the moving resistance force. (2) can be re-arranged:

$$a = \frac{F-R}{m} - g \times \sin\theta \tag{3}$$

It can be noticed from (3) that the vehicle acceleration is inversely proportioned to the vehicle mass. However, the acceleration is a function not limited to mass but also to driving force, resistance force and road inclination angle. Assuming that the proposed system is calibrated (trained) in similar road environments, the acceleration values can be a good representative of vehicle mass. As a result, the acceleration measurements can be used to capture vehicle weight. The proposed machine learning approach is used as a classifier function to map the acceleration measures with weight class after training.

## 2.3. Smartphone inertial sensors and vehicle sensors

Smartphone using is increasing dramatically in the last few years. Smartphones are equipped with many built-in sensors that are used to manage smartphone functionality. Accuracy and quality of these sensors usually depend on smartphone brand and price. In this work, we are focusing on sensors affected by motion. Motion-related sensors which are embedded in smartphone are accelerometer and gyroscope. Figure 2 shows an example of smartphone and graphical representation of the two motion sensors (accelerometer and gyroscope) and will be described in more details next subsections



Figure 2. Smartphone and its inertial sensors

### 2.3.1. Accelerometer

Accelerometer is a device used to measure acceleration that is manufactured using micro-electro-mechanical systems (MEMS) technology. Recently, majority of smartphones are equipped with tri-axial accelerometer as illustrated in Figure 1 where the orientation of accelerometer axes is aligned with smartphone body. In this work, it is not necessarily to align the smartphone body with vehicle heading. Acceleration is an essential motion metric which proportions inversely with mass as Newton's second law says [19]. Several vehicle dynamic measures can be affected directly by vehicle mass and these measures can be captures by accelerometer (and gyroscopes) devices [25]. A brief description of these measures is listed.

a)  Suspension dynamics: Vehicle suspension system carries load and vehicle mass against gravity force. Also, this system is responded directly to vertical vehicle inertia changes while driving status. All these changes can be captured by accelerometer.

b)  Lateral/yaw dynamics: Due to vehicle manoeuvring or turning, lateral forces appear in a magnitude that is directly proportional to vehicle mass. These forces can be easily captured by tri-axial accelerometer (and gyroscope).

c)  Longitudinal dynamics: Vehicle engine generates certain amount of traction power and force. Consequently, the longitudinal acceleration and deceleration (or braking) relate directly to the effective mass of vehicle. The changes in vehicle speed can be effectively captured by accelerometer measures.

### 2.3.2. Gyroscope

Gyroscope is a MEMS sensor that smartphone is equipped with. It is used to measure angular velocity and usually to maintain orientation. Similar to accelerometer structure, gyroscope also has three axes component usually named roll, pitch and yaw according to the rotation axis (Y, X or Z respectively) as illustrated in Figure 1. Again, in this work the alignment of smartphone inside the vehicle is not a crucial point because reflection of vehicle mass changing can be captured by either of the gyroscope components. Vehicle turning and maneuvering (Lateral/yaw dynamics) causes changes in the angular velocity of the vehicle. These changes can be effectively recorded by smartphone gyroscope sensors when it is located inside the vehicle.

## 3.    THE PROPOSED APPROACH

The proposed weigh-in-motion approach is described and overviewed in this section. This approach includes four stages as shown in Figure 3. These stages are started with the experiment and data collection, pre-processing, feature extraction, and finally classification stage. In this section these stages will be detailed in subsection as follows:
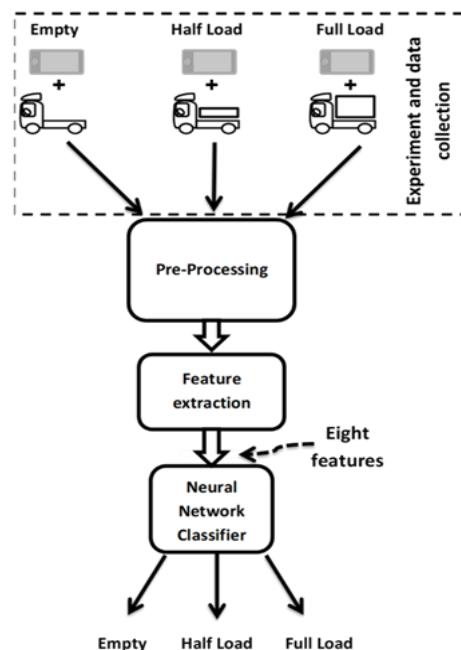


Figure 3. The proposed approach

### 3.1. Experiment and data collection

A small truck (pick-up truck) is used in this work to conduct the experiment and to collect data from smartphone. The full load capacity of the used vehicle is 1000 KGM. A local road of around 1 Km long is chosen to do the experiment which is usually a busy road to enhance the experiment with realistic vehicle behaviour. Low-cost smartphones (Xiaomi Redmi 5 and Sony Xperia Z3) are used in this experiment to test the ability of the solution to work with any type of smartphone. Numerous sensors are equipped with this smartphone. However, three sensors have been chosen in this work and they are; Accelerometer, Gyroscope, and Magnetometer.

Three loading levels are chosen in this work to test the ability of the algorithm to distinguish between them. These levels are empty, half load, and full load levels. Six trips with the truck are traveled while the smartphone is collecting data from its built-in sensors using the mentioned application. Every two trips have been represented one of three load levels. The smartphone has been used as a data logger with aid of a commercial application named sensor kinetics pro [26]. The application can collect all built-in smartphone sensors. In this work, three movement sensors (accelerometer, gyroscope, and rotation virtual sensors) have been selected to share their data.

### 3.2. Pre-processing

Different sources of noise commonly contaminate the collected data. The common method to reduce the effect of inertial sensors noise is to use a moving average window filter [27]. The window size of the moving average filter is depending on the sampling rate and time response of the vehicle. For this work, a window size of 60 samples is chosen to trade-off between the sampling rate (200 Hz) and the time response of vehicle activity (acceleration and deceleration). This selection has been chosen to achieve maximum classification (next stage) performance.

Pre-processing stage is added to reduce the noise effect and prepare data for the feature extraction stage. Figure 4 shows an example of this job. It is clear that noisy filtered raw (grey color) has been filtered and present in clearer form (black line) which is ready to feature extraction stage. Moreover, several time slots of data have been removed from the dataset when the vehicle is in idle status because this work is proposed to measure weight in motion. When the vehicle is in movement status, inertial sensors can capture vehicle behaviour including weight effect. However, this is not the case when the vehicle is in idle status.

Figure 4 shows several acceleration and deceleration tie intervals which are presented as positive and negative acceleration values respectively. Changes in inertial sensor behaviour capture changes in vehicle activity. These changes are used to capture the effect of vehicle mass on its behaviour.

Vehicle dynamics quantities such as acceleration, braking, cornering, and inertia have a direct relation with vehicle mass. Acceleration and braking have a proportional inverse relation to vehicle mass as stated in Newton's second law of motion. So, inertial sensors which are functioned based on the same principles can capture changes in vehicle mass. Figure 5 shows an example of collected data belongs to three load levels of the vehicle under test.
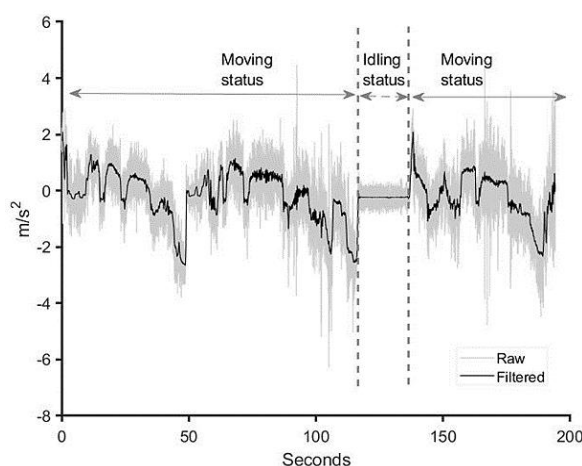


Figure 4. An example of pre-processing stage with raw and filtered data imposed on same graph and showing different vehicle movement statuses
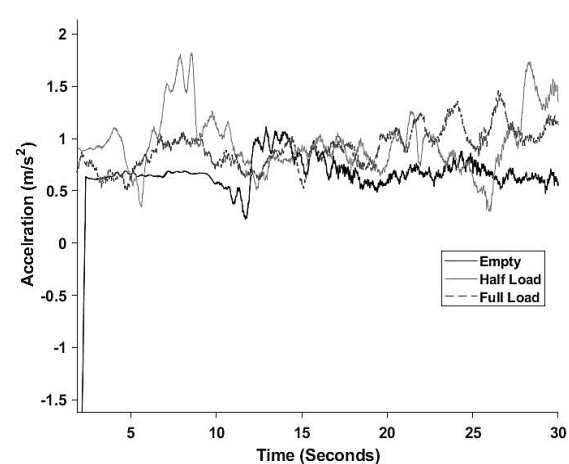
Figure 5. An example of filtered data imposed on the same graph showing different vehicle loading levels

### 3.3. Feature extraction

The pre-processed data has been statically analyzed to the first and second momentum levels. Two hardware built-in sensors (accelerometer and gyroscope) and one software computed sensor (rotation) are selected to generate features. Many combinations sets of features tested and the set with the best classification performance have been chosen. The selected feature set includes eight features and they are:

(1) X component of accelerometer.
(2) Y component of accelerometer.
(3) Z component of accelerometer.
(4) Magnitude of gyroscope.
(5) Magnitude of rotational sensor.
(6) Standard deviation of acceleration magnitude.
(7) Standard deviation of gyroscope magnitude.
(8) Standard deviation of rotation magnitude.

These features are extracted and stored in a database of 42000 records. Each record includes 8 values from the aforementioned sets. This features dataset is used to feed the neural network classifier (next subsection). This dataset is labeled with three labels (empty, half load and full load) according to trip status.

### 3.4. Neural network classifier

Neural network is widely used as a machine learning technique. It is used mainly when there is a complex relationship between input and output relation and it can capture the pattern and classify it based on a previous learning phase [28]. In this work, the neural network is used to classify one of three classes based on a set of eight previously mentioned features. The structure of the neural network consists of three layers; the input layer with eight neurons and the hidden layer with twenty neurons and finally the output layer with three neurons to simulate the three classes. The features dataset is divided into three subsets including 60% of data as training subset, 20% as a testing subset and 20% as validation subset.

## 4. RESULTS AND DISCUSSION

The ternary (three classes) neural network (NN) classifier is designed and tested with different hidden layer neuron numbers. The feature dataset is fed to the input layer of NN classifier and the performance metrics are calculated based on data gained from the output layer. The receiver operating characteristic curve (ROC) is commonly used to test classifier performance metrics [29]. This ROC for the implemented classifier is shown in Figure 6 and it illustrates the three classes performance with three different line types. The area under this curve (AUC) is a sign for classifier accuracy. It is noticeable the three classes have presented good accuracy since the AUC for the three classes is close to 1 (the perfect classification results). However, the "empty" class shows the best AUC and best classifying results, which is expected, because the vehicle moving behaviour will be much more different than the other two classes. When the vehicle is empty, it accelerates and decelerates faster than when it is loaded. The ROC graph which is shown in Figure 6 Illustrates graphically the classification results.

Another classification performance metric is the confusion matrix (CM). This metric tends to present data in numbers form rather than graphical form (as in ROC). The confusion matrix of the implemented classifier is presented in Figure 7. The confusion matrix depicts a clear overview of the classifier results. The diagonal numbers of CM show the correctly classified samples which is in our case the major part of the dataset. However, there is still a small fraction of data is misclassified between the three classes.

The best classification rate is gained by the first class (empty class) which is scored 97.3%. This result happened because of the damping, acceleration and declaration of vehicle, in this class, is significantly different from other classes when the vehicle is loaded. However, the overall accuracy of the three classes is 91.2% that shows the ability of this approach to classify correctly the load level of the tested vehicle. Error tolerance of implemented approach (8.8%) is within permissible error limit (5-15%) [20]–[22].

The classifier performance metrics are listed in Table 1. Again, the best accuracy is granted to the first class ("empty class") as discussed earlier. Precision and recall are another performance metrics that are calculated based using the confusion matrix. These two metrics give another perspective to classifier results in companion with accuracy. The precision shows close results (around 0.9) for the three classes which is a sign for the classifier to work consistently for all classes. The recall metrics which is sometimes called sensitivity, aims to capture the maximum number of instants belongs to that class. It is clear from recall numbers that the first class has the highest number. It seems that the data of this class can easily distinguish from the other two classes. Finally, F1 score is a single score that can balance precision and recall as its numbers seem to be the average of the other two metrics.
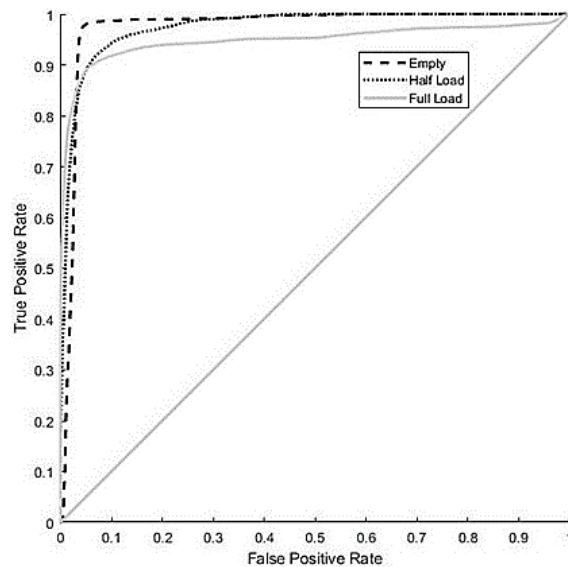
Figure 6. The Ternary NN classifier ROC and AUC performance metrics



Figure 7. The Ternary NN classifier confusion matrix

Table 1. Classifier performance metrics

| Class | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Empty | 96.26% | 0.92 | 0.97 | 0.95 |
| Half load | 93% | 0.9 | 0.89 | 0.89 |
| Full load | 93.11% | 0.92 | 0.87 | 0.89 |

Many research papers had been investigated WIM systems to improve their performance. The improvement usually aims to enhance cost, complexity, accuracy, and frequency of calibration. However, the proposed approach (using smartphone inertial sensors only) is not adopted in these research papers. Although the accuracy is within error tolerance of existing systems (5-15%), the accuracy is not one of the best results of the proposed approach. However, other evaluation metrics can be count for this approach. The proposed WIM approach is cost-effective compared to the existing system since it uses only smartphone embedded sensors. Also, after training, there is no need for calibration which is essential feature for such systems. Finally, the proposed WIN approach is easy to use and implement in any vehicle and there is no need for experts for installation. Table 2. Shows a comparison between the proposed and existing systems based on most known evaluation metrics.

Table 2. Comparison between existed technologies and the proposed approach

| WIM technology | Cost | Complexity | Accuracy | Frequency of calibration | Sensors type |
|---|---|---|---|---|---|
| LS-WIM | High | High | Moderate | Moderate | Load cell/Bending plates |
| HS-WIM | High | High | Low | High | Accelerometer/strain gauge |
| **Proposed WIM** | **Low** | **Low** | **Low** | **low** | **Smartphone sensors** |

## 5. CONCLUSION

A new approach for on-road vehicle weighing scales using smartphone inertial sensors is proposed in this work. The proposed WIM approach has been planned, designed and implements successfully. This approach is achieved based on smartphone inertial sensors (accelerometer and gyroscope) and rotational sensor using an existing data collection application. These sensors can capture the dynamic behaviour of the vehicle. The approach has been tested through a small truck with six trips (two trips for each class). The approach is designed to distinguish the vehicle load among three classes (empty, half load and full load). The classifier performance results proved the successful rate of implemented approach to identify the actual class load with an accuracy of 91.2%. The results show the ability of the implemented approach to estimate the actual load of the moving vehicle without the need for any extra onboard hardware. More development can help to make this approach more practical by increasing the classes of vehicle load.

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