Artificial Intelligence-Driven All-Terrain Vehicle Crash Prediction and Prevention System

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HIGHLIGHTS

- An AI-driven system for predicting and preventing ATV crashes was developed.
- Machine learning model achieved rollover prediction accuracy of over 99%.
- The system has the potential to significantly reduce ATV-related injuries and fatalities by enabling preemptive actions.

ABSTRACT. *All-Terrain Vehicle (ATV) crashes have become a public health concern in the U.S. over the past decades, resulting in numerous fatalities and hospitalizations. Most of those incidents could have been prevented if riders could better assess their ability to handle risks. Currently, risk factors associated with ATV incidents have already been studied. However, little effort has been made toward developing practical applications that assist the rider in preventing crashes. Commercial ATV safety systems, such as Farm Angel, focus on post-crash detection and emergency medical services (EMS) alerting rather than preventive measures. Machine learning prediction models can be used to assist riders in taking preventive measures to avoid an imminent crash. In this study, we developed a system that leverages the predictive power of machine learning algorithms to assess the likelihood of a crash in real-time and alert the riders, thus allowing them to prevent the crash. To the best of our knowledge, this is the only system ever developed for ATVs specifically that can predict rollover incidents. The crash likelihood is estimated by a deep neural network that considers the ride parameters (e.g., ATV speed, turning radius, and roll and pitch angles), ATV characteristics (e.g., width, length, wheelbase), and human factors (i.e., presence of a rider). The ATV characteristics and the presence of a rider are retrieved from the rider's input through a smartphone application developed specifically for this study. The ride parameters are retrieved from an embedded system (attached to the ATV). Validation and performance tests indicated that: (1) the proposed device has a rollover prediction system with an accuracy superior to 99%; (2) the system can detect roll and pitch angles with average errors of 0.26 and 0.54 degrees, respectively; and (3) the system can detect the ATV's speed with an average error of 0.75 m s^{-1}.*

Keywords. *ATV safety, Crash prediction, Machine learning, Rollover prevention.*

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Deaths and injuries due to All-Terrain Vehicle (ATV) crashes are a significant public health concern in the U.S. (Jennissen et al., 2016). Approximately 700 people die, and another 90,000 visit an emergency department (ED) every year due to ATV-related injuries within the U.S. (Topping, 2018). Furthermore, the average hospital charges associated with ATV-related injuries was estimated at $45,582 per patient (Miller et al., 2020). As a result, a total of $4 billion per year of hospital charges is estimated from the total annual number of ED visits due to ATV-related injuries within the U.S. (Topping, 2018). Typical ATV crash types include collisions and rollovers (Balthrop et al., 2007; Denning et al., 2013; Hall et al., 2009; Helmkamp et al., 2011). Most of those crashes could be prevented if riders did not misjudge their ability to detect and manage risks (Carman et al., 2010; Cavallo et al., 2015; Clay et al., 2015; Denning and Jennissen, 2016). Thus, predicting a crash ahead of time and warning the rider seems to be of utmost importance.

Common solutions for improving the safety of motorized vehicles (i.e., automobiles, tractors, and ATVs) consist of crash detection and notification systems like Onstar (2022) and Farm Angel (2022). However, those systems are limited because they cannot warn the rider ahead of time; thus, riders cannot prevent the crash.

In contrast, crash (i.e., collision or rollover) prediction systems aim to foresee a crash and alert the rider ahead of time so that the incident can be prevented. Collision prediction systems are mainly used for automobiles, while in agriculture most of the research efforts address farm machinery such as tractors (Previati et al., 2014; Watanabe and Sakai, 2019). Regardless of the crash type, conventional crash prediction systems often consist of expensive sensors such as radar, light detection and ranging (LIDAR), cameras, and Global Positioning System (GPS) (Fu et al., 2020; Guo and Yue, 2014; Guzmán et al., 2011; Xiang et al., 2014). An alternative cheaper solution consists of using crash prediction models. Collision prediction models are based on vehicle motion and dynamics, such as physics-based (Berntorp, 2016; Joerer et al., 2014; Xie et al., 2018), maneuver-based (Aoude et al., 2011; Xie et al., 2018), and interaction-aware models (Chiang et al., 2014; Hafner et al., 2013). These models aim to combine the state (location, orientation, speed, and acceleration) of multiple vehicles to project their trajectory and predict the likelihood of a collision.

Similarly, rollover prediction models exist, mainly based on the vehicle's center of gravity (CG) and terrain slope angles (roll and pitch) (Rath et al., 2016; Solmaz et al., 2007; Yim, 2011; Yim et al., 2010; Zhang et al., 2017). Although collision and rollover prediction algorithms have considerably improved crash avoidance, they have several limitations. For instance, as of 2024, no models were developed for ATVs, which have significantly different dynamics from automobiles and tractors. Moreover, vehicle state-based models require data from multiple vehicles; for example, there must be a continuous information exchange, which makes this approach vulnerable to communication errors (Kim et al., 2019).

To overcome the outlined issues, there are many crash prediction algorithms based on artificial intelligence (AI) that do not require any assumptions. Previous studies demonstrated that such algorithms can be trained to mimic how humans drive automobiles and perceive the scene; for example, they pay attention to key details such as lane, markings, nearby vehicles (Fu et al., 2020; Kahn et al., 2017; Sugathan et al., 2017), and terrain surface (Sanchez et al., 2004). However, to the best of our knowledge, no AI-based rollover prediction models have been developed specifically for ATVs. Additional studies are needed to develop AI-based prediction models that directly aid operators in preventing ATV rollovers (Van Ee et al., 2014).

The study's long-term goal is to decrease the severity of injuries and the number of fatalities in ATV-related incidents. The objective of this study, which is a step towards attaining our long-term goal, is to develop an ATV rollover prediction system. This system aims to prevent crashes by alerting users of dangerous riding conditions ahead of time. The objective of this research was achieved based on the following specific aims:

(a) Develop a machine learning model to predict the likelihood of an ATV rollover based on the ride parameters (e.g., ATV speed, roll and pitch angles, and turning radius.), vehicle characteristics (e.g., weight, track width, height, wheelbase, etc.), and the human factor (presence or not of a human riding the ATV);
(b) Develop a smartphone application to collect the ATV characteristics based on user input;
(c) Develop an embedded system (to be installed on the ATV) to monitor the ride parameters (e.g., speed, attitude, and acceleration);
(d) Implement the rollover prediction model (a) in the embedded system (b) to predict the likelihood of a rollover in real-time and alert the rider if the model output is above a predetermined threshold.

Materials and Methods

The rollover prediction system developed in the present study consists of an embedded data logging system, a control unit, and a smartphone application (iOS). The embedded system was used for two main tasks: (1) monitor and record ATV riding parameters (e.g., vehicle's speed, pitch and roll angles, and turning radius); and (2) automatically trigger an emergency alert when dangerous riding conditions were detected (i.e., high likelihood of rollover event). The smartphone application was developed to allow users to input their ATV data. In the following sections, we describe the rollover prediction algorithm, the embedded system for data collection, and the smartphone application for user input.

Rollover Prediction Algorithm

A classification model based on machine learning (ML) algorithms was developed and implemented in the embedded system. This algorithm calculates the likelihood of a rollover event based on the ride's parameters (vehicle's speed, roll, pitch, and turning radius) and the ATV model (weight, height, width, wheelbase, and seat height). Suppose the probability of a rollover event is greater than a certain (adjustable) threshold (for the present manuscript, we chose this threshold to be 50%). In that case, the system issues an audiovisual alert consisting of a high-intensity red LED and a piezo buzzer. To the best of our knowledge, this is the first algorithm developed to predict the likelihood of a rollover for ATVs specifically.

A dataset containing 51,700 samples was used to create the classification model. The samples were retrieved directly from available sources (Hicks et al., 2019; Mongiardini et al., 2014) and created based on previous studies (Auxier, 2020; Grzebieta et al., 2015a,b). The dataset consisted of observations from mathematical simulations, finite element analysis (FEA), and realistic simulations, including static and dynamic tests. For the samples consisting of mathematical simulations and FEA, the rollover occurrence was instantly calculated based on input variables, such as vehicle speed, slope roll angle, and bump height. For the samples consisting of realistic simulations (static and dynamic tests), the occurrence of a rollover was determined by a human observer. The dataset consisted of fourteen ATV models under diverse riding scenarios, including terrain slope (0, 5, 10, 15, 20, and

25 degrees), vehicle speed (5 to 50 km h^{-1} in installments of 2.5 km h^{-1}), and turning radii (5 to 50 m in installments of 2.5 m). The presence (or not) of a rider was also considered in the model since several rollover tests are performed without a rider for safety purposes. Each sample was classified as either non-rollover (0) or rollover (1). Detailed information about the input variables and their units is presented in table 1.

The dataset was first normalized (z-transformation) and then split into three subsets for training (60%), cross-validation (20%), and testing (20%).

Four classification algorithms were tested: K-nearest neighbors (KNN), Random Forest, Support Vector Machine (SVM), and Deep Neural Network (DNN). These four classification algorithms were chosen based on their widespread usage, unique strengths, and diverse underlying mechanisms, which could potentially yield different insights for our problem space. The algorithms were developed from the packages sklearn (Pedregosa et al., 2011) and Keras (François, 2015), which are machine learning packages for Python (programming language). In addition, several tuning parameters, such as learning rate, momentum rate, and stop criteria, were tested based on the recommendations of a previous study (Ferreira et al., 2017). The output of each model consisted of a binary variable (0 – if no rollover was predicted, or 1 if rollover was predicted). A summary of tuning parameters for the algorithms is presented in table 2.

Embedded Data Logging System and Control Unit

A Raspberry Pi 4 Model B (RPi, 4GB) single-board computer (Adafruit, New York, NY, USA) was used to retrieve data (roll and pitch angles and speed) from the GPS and IMU and feed these data to the rollover prediction algorithm. The RPi uses a 1.5GHz 64-bit quad-core Arm Cortex-A72 CPU and has 802.11 ac/n wireless Local Area Network (LAN), and Bluetooth 5.0. In addition, the RPi has several ports for communicating with peripherals, including HDMI, USB, SD Card reader, and general-purpose input/output (GPIO) pins. A portable battery (Anker PowerCore II 20000) was used to supply power to the system. When the ATV engine was on, the ATV's battery was used to recharge the portable battery.

The ATV's roll and pitch angles were measured with an Inertial Measurement Unit (IMU – model LSM9DS1, manufacturer: Adafruit). To improve the accuracy and robustness of those measurements, a Madgwick filter (Madgwick et al., 2011) was implemented. This filter fuses gyroscope, accelerometer, and magnetometer measurements to calculate

Table 1. Prediction model's input variables and description.

Input Variable	Unit	Description
ATV weight	kg	ATV net weight (no rider and fuel tank empty)
Width	mm	Measured from left to right across the widest part of the ATV, including tires but not including any side mirrors
Length	mm	Measured from front to rear across the longest part of the ATV
Wheelbase	mm	Measured between the center of the front and rear wheel hubs from the same side
Seat height	mm	Measured from the ground up to the ATV seat center
Speed	km/h	ATV's last recorded speed before the incident
ATV pitch angle	degrees	ATV's last recorded pitch before the incident
ATV roll angle	degrees	ATV's last recorded roll before the incident
Turning radius	m	Calculated as the tangential speed (in m/s) divided by the yaw rate (in radians/s)
Presence of a rider	(binary score - 0 if none, or 1 otherwise)	Part of the data used to train the classification algorithm consisted of autonomous ATVs without any riders

Table 2. Classification algorithms tuning parameters.

Algorithm	Parameter	Values
KNN	n	5, 7, 9, 10
Random Forest	Number of trees	100, 200, 250, 300
	Maximal depth	10
SVM	Kernel function	linear, polynomial, radial basis function, sigmoid
	C	2^{-3}, 2^{-1}, 2
	γ	2^{-13}, 2^{-11}, 2^{-9}, 2^{-1}
DNN	Activation	ReLU
	Hidden Layers (neurons)	2 (32/32)
	Model Optimizer	Adam
	Epochs	100

the vehicle's attitude (roll, pitch, and yaw). The vehicle's attitude is initially estimated by integrating gyroscope measures, which inherently yields drift in the long term. The long-term drift from the gyroscope integration is compensated by the accelerometer estimates of attitude. The magnetometer measures are used to compensate for magnetic distortions from potential sources of interference around the sensor, such as electrical appliances (for instance, a GPS sensor) and metal structures (e.g., the ATV's frame).

The ATV's speed was calculated based on the measurements of a Global Positioning System (GPS – model Ultimate GPS Breakout v3, manufacturer Adafruit) and the LSM9DS1 IMU through an Unscented Kalman Filter (UKF) (Brossard et al., 2020). The UKF is a non-linear version of a Kalman Filter (Gomez-Gil et al., 2013; Kalman, 1960), which is an algorithm that combines multiple sensor information to estimate the state of a system, such as the vehicle's position and speed (Leung et al., 2011). The fundamental advantage of the UKF over the Kalman Filter is that it works for non-linear systems, which is the case for most robots and sensors (Vougioukas, 2019). Due to the environment of some ATV off-road crashes (e.g., dense woods), GPS signals might be unavailable or yield inaccurate measures. To address this issue, IMU data (which allows continuous position tracking) can be fused with GPS data through the UKF.

Communication between the IMU and the RPi was implemented via a Serial Peripheral Interface (SPI) connection, and the communication between the GPS and the RPi was implemented through a Universal Asynchronous Receiver Transmitter (UART) GPIO pin.

Lastly, the ATV's turning radius was calculated based on its tangential speed and yaw rate, as shown in equation 1.

$$TR = s \, / \, yr \tag{1}$$

where

TR = ATV's turning radius in m

s = ATV's speed in m s^{-1}

yr = ATV's yaw rate in radians.s^{-1}.

All the electronic components of the embedded system were placed inside a custom-manufactured enclosure, resistant to vibration and dust, which was installed on the rear rack of the ATV. The GNSS antenna was attached to the ATV front chassis.

Embedded System Performance Assessment

We performed tests to evaluate the accuracy of pitch, roll, and speed estimates. In the following two sub-sections, we describe these tests.

Roll and Pitch Angles

The estimates of roll and pitch angles were validated based on the measurements of a standard device (H6 Digital Inclinometer, manufacturer Rieker Inc.). Manufacturer-certified calibration was performed before data collection with the standard device. For each variable (roll and pitch), 30 angle values were randomly selected to assess the system's performance. The choice of the number of observations was due to its practical feasibility and because it is a sufficient sample size to perform meaningful statistical analysis, ensuring that the results are reliable and not due to random chance.

The IMU was manually tilted and kept at the selected angles. The deviation in degrees obtained by the IMU module from the digital inclinometer was calculated using the Euclidian distance, as presented in equation 2.

$$\overline{A} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(\theta_{IMU\,i} - \theta_{inclinometer\,i}\right)^2} \tag{2}$$

where

$\overline{A}$ = mean deviation in degrees from the IMU to the digital inclinometer (standard device)

n = number of observations (n = 30)

$\theta_{IMU\ i}$ = angle measured by the IMU in degrees

$\theta_{inclinometer\ i}$ = angle measured by the digital inclinometer in degrees.

Speed

The system's estimates of speed were evaluated in a study of the ATV model Honda Rancher 4x4 (2018). The study ATV was equipped with the RPI, the Ultimate GPS Breakout v3 GPS, the LSM9DS1 IMU, and a Real-Time Kinematic GNSS receiver (RTK – model Piksi Multi GNSS, manufacturer Swift Navigation). To maintain a constant speed during the experimental trials, the ATV was equipped with a QuadCruise control unit (MC S2580E, MCCruise). The control unit of the cruise control system consists of a computer unit, an electric throttle servo, a cable interface unit (CIU), and a Bluetooth module for remote controls (MCCruise, 2018). More information about the installation and operation of this device is available in a previous study (Chou et al., 2022). The system mounted on the ATV is illustrated in figure 1.

Although the QuadCruise controlled the ATV speed remotely, an operator was always riding the vehicle for safety purposes. The vehicle was accelerated to the desired speed (which was adjusted by the operator) and then ridden for at least 10 s to allow the GPS module to track a stable velocity (fig. 2). Three pre-set speeds were evaluated: 2.23, 3.57, and 5.36 m s^{-1} (5, 8, and 12 mph, respectively), with three replicates for each speed. The system's average speed error was calculated according to equation 3.

$$\overline{S} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\left(S_{system\,i} - S_{RTK\,i}\right)^2} \tag{3}$$

where

$\overline{S}$ = mean speed error in m s^{-1}

n = number of observations

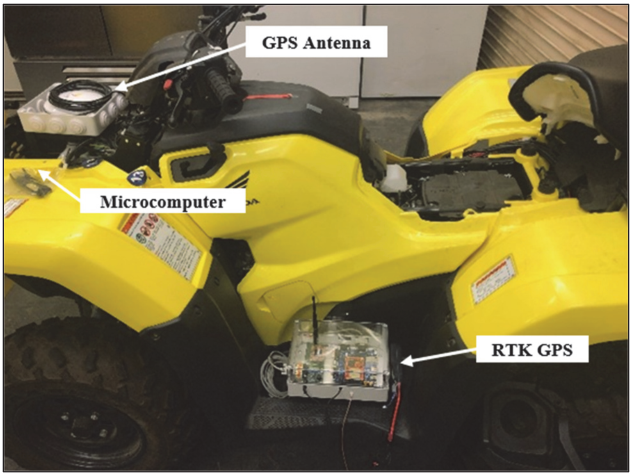


Figure 1. Honda Rancher 4x4 (2018) fitted with the embedded system.

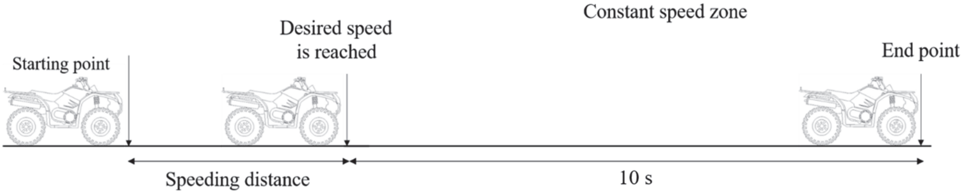


Figure 2. Schematic of the procedure to evaluate the system speed estimate performance. Source: Khorsandi et al. (2024).

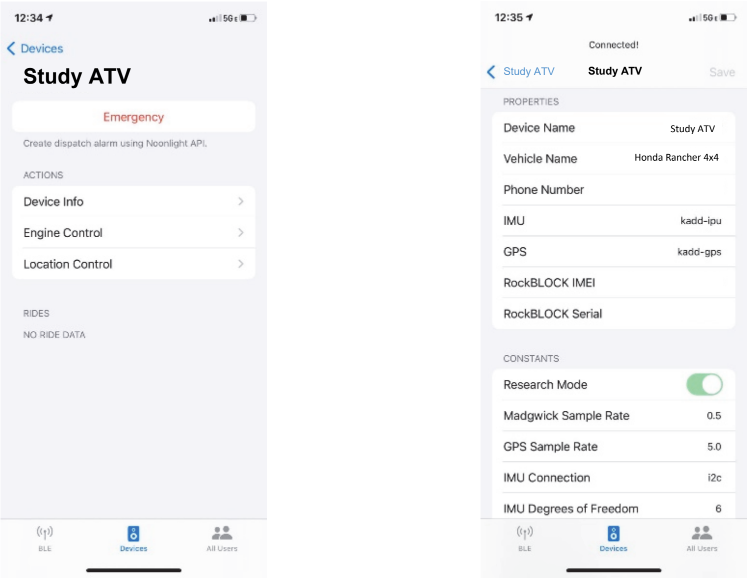
$S_{system\ i}$ = speed measured by the system (combination of GPS and IMU data fused through a UKF) in m s^{-1}

$S_{RTK\ i}$ = speed measured by the RTK in m s^{-1}.

Most observations occurred out of the constant speed zone (e.g., start/end of data collection with ATV stationary, speeding zone), which could add bias to the estimation of $\overline{S}$, since the number of observations outside the constant speed zone is higher than the number of observations in the constant speed zone. For this reason, only observations in the constant speed zone were used in the calculation of $\overline{S}$.

Smartphone Application

The smartphone application (fig. 3) was developed using the Swift language, which is the primary programming language for iOS app development. To enhance the users' experience, customized features and functionality were implemented in the app through Cocoapods, which is a dependency manager for Swift. Cocoapods was built with the Ruby programming language, which allows packages to be installed and used in the original Swift application. The communication between the smartphone application and the RPi occurs through a proprietary Bluetooth Low Energy (BLE) communication protocol, which provides fast data access.



(a) **(b)**

Figure 3. iOS application interface. (a) Vehicle's menu, (b) Vehicle information.

Data Analysis

In this section, we describe the metrics and benchmarks adopted for the rollover prediction algorithm, roll and pitch angles, and vehicle speed.

Rollover Prediction Algorithm

The performance of each algorithm was evaluated by the area under the curve (AUC) of the receiver operating characteristic (ROC) (Lee et al., 2017). The ROC curve is represented by a plot of the true positive rate against the false positive rate. Moreover, AUC is a measure of the two-dimensional area underneath the ROC curve, in which its value ranges from 0.0 to 1.0. The algorithm with the highest AUC score was implemented in the RPi for predicting the likelihood of a rollover event. In the case of a tie, the algorithm with the highest F-score (Wood, 2020) and balanced accuracy was selected. F-score is a measurement that combines both precision and recall into a single expression, giving each equal importance, and it is calculated as:

$$F = 2\frac{\text{precision. recall}}{\text{precision} + \text{recall}} \tag{4}$$

where precision is defined by the number of true positives divided by the sum of true positives and false positives, and recall is the number of true positives divided by the sum of true positives and false negatives.

Balanced accuracy is defined as the average between recall and specificity, which is the number of true negatives divided by the sum of true positives and false positives.

Roll and Pitch Angles

The benchmark adopted for the average angle estimate error was 1.0 degrees. This benchmark was calculated as 50% of the accuracy of the standard measurement device (digital inclinometer). According to the equipment datasheet, this device has an error of 0.5 degrees (Rieker Inc., 2019).

The null hypothesis ($\bar{A} \leq 0.5$ degrees) was tested through a t-test with a strict significance level of 1% ($\alpha = 0.01$), reflecting the high level of confidence required for the system to accurately estimate the occurrence of rollover incidents, given the critical safety implications.

Vehicle Speed

The benchmark adopted for the average speed error was 1.0 m s^{-1}. Although the desired outcome may seem well below the accuracy delivered by advanced GPS devices/tracking algorithms, very high accuracy is not critical for the success of this system. For instance, the speed intervals from the data used to train the rollover prediction algorithm were 1.39 m s^{-1} (5 km h^{-1}). The null hypothesis ($\bar{S} \leq 1.0$ m s^{-1}) was tested through a t-test with a significance coefficient of 5% ($\alpha = 0.05$).

Results

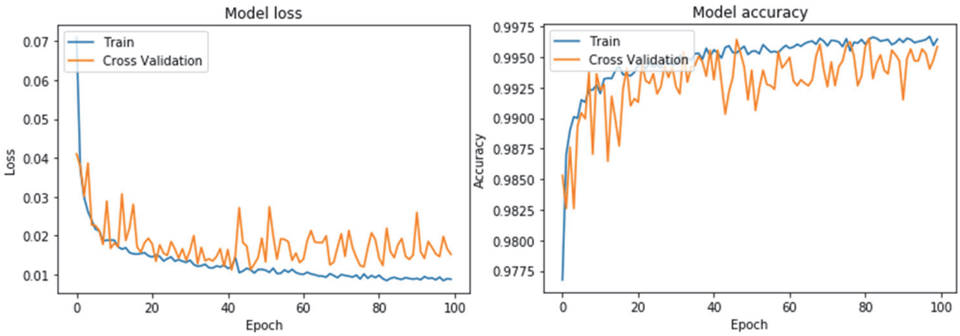
Rollover Prediction System

A summary of the performance of the top ten classification models is presented in table 3. The results indicate that the trained models can predict rollover with reasonably high accuracy (> 99%). The model with the highest AUC, F-Score, and balanced accuracy was the Deep Neural Network, with two fully connected hidden layers (32 neurons in each) and ReLU activation function.

The learning curves for the selected model (Rank #1) are presented in figure 4. The learning curves indicate that neither underfitting nor overfitting has occurred, as no increase was detected in the cross-validation loss values and both train and cross-validation loss values at epoch 100 were low (< 0.02) and close to each other. In total, 1,474 parameters were trained over a dataset containing 31,020 samples. The model achieved accuracy superior to 99.5% using a testing dataset containing 10,340 samples. Furthermore, the model's balanced accuracy (0.993) and F-score (0.976) indicated that the imbalanced dataset did not represent a problem.

Table 3. Performance summary of the classification algorithms.

Rank	Algorithm Type	Combination of Parameters	AUC	F-Score	Balanced Accuracy
1	DNN	Activation = ReLU; Layers (neurons): 2 (32/32); Optimizer = Adam; Epochs = 100	1.000	0.976	0.993
2	SVM	C = 2, gamma = 0.2, kernel = rbf	1.000	0.974	0.991
3	Random Forest	Number of trees = 300	0.999	0.955	0.987
4	Random Forest	Number of trees = 200	0.999	0.955	0.987
5	Random Forest	Number of trees = 100	0.999	0.958	0.987
6	Random Forest	Number of trees = 250	0.999	0.954	0.986
7	SVM	C = 0.2, gamma = 0.2, kernel = rbf	0.999	0.946	0.985
8	SVM	C = 2, gamma = 0.2, kernel = poly	0.999	0.974	0.991
9	KNN	Number of neighbors = 10	0.998	0.941	0.984
10	KNN	Number of neighbors = 9	0.998	0.951	0.986



(a) (b)

Figure 4. Rollover prediction algorithm learning curves. (a) Model loss; (b) Model accuracy.

Angle Measurements

A summary of the system's performance in measuring roll and pitch angles is presented in figure 5. The average angle estimate error for the roll and pitch angles were 0.26 ± 0.07° and 0.54 ± 0.11° (95% CI), respectively. These values are significantly smaller than our selected benchmark of 1.0° (p-value < 0.001). Despite the low cost of the sensors in the system, it was possible to estimate the vehicle's roll and pitch angles with reasonable accuracy.

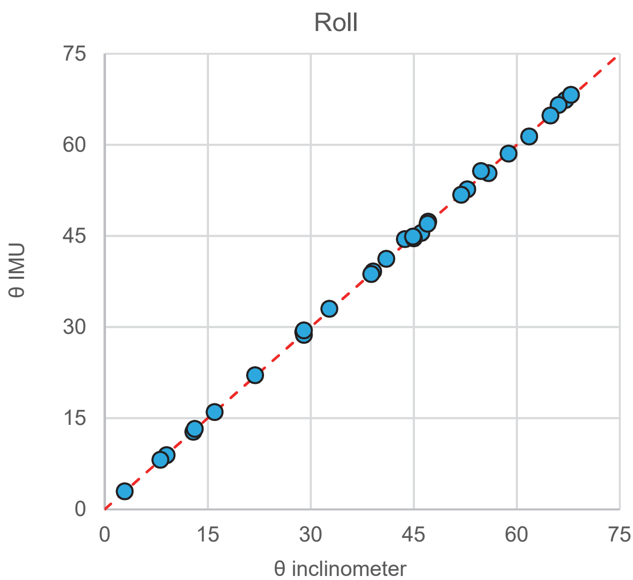
Vehicle Speed

The average speed estimate error for the speeds of 2.23, 3.57, and 5.36 m s^{-1} were 0.77, 0.63, and 0.88 m s^{-1}, respectively (table 4). Moreover, the average error across all observations was 0.75 ± 0.02 m s^{-1} (95% CI). These values are significantly smaller than our selected benchmark of 1.00 m s^{-1} (p-value < 0.001). Despite the lower precision compared to the state-of-the-art tracking devices, it is possible to use this low-cost system to estimate the vehicle's speed with reasonable accuracy, as illustrated in figure 6.

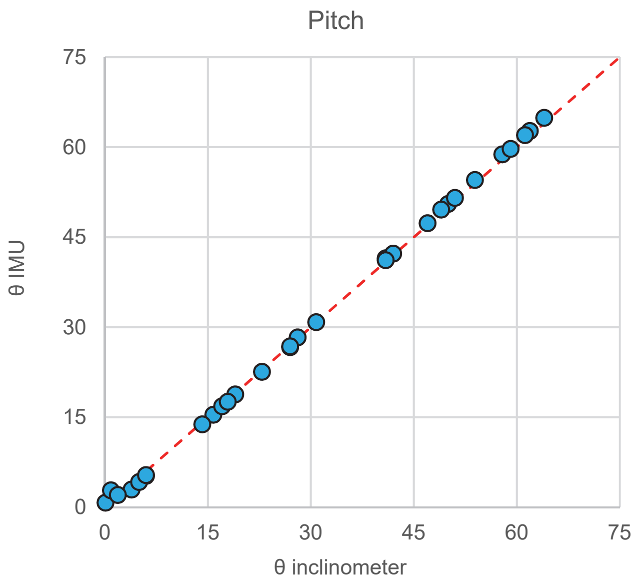
Discussion

During the process of data curation, it was observed that the dataset was imbalanced (about 85% of the samples consisted of non-rollover examples). The disparity in the number of samples of each class could potentially affect the model's accuracy. However, we deemed that it would be best not to alter the dataset before training a prediction model because even though there is great disproportion, the number of classes is minimal (only 2), and the absolute number of samples in each class is high. Furthermore, instead of assessing the prediction model's performance through its overall accuracy, we evaluated its balanced accuracy and F-score, which are frequently used measures to assess prediction models trained on imbalanced data (Haibo and Garcia, 2009).

Our research explores the use of different classification algorithms, each with their own unique underlying mechanisms, to predict ATV crashes and alert the riders ahead of time. Overall, the DNN model outperformed the KNN, SVM, and Random Forest models, achieving accuracy superior to 99.5%. When compared to other modeling techniques, such as mathematical simulations or finite element analysis, the DNN model stands out by its simplicity and rapid processing time. The developed model utilizes easily obtainable



(a)



(b)

Figure 5. Angle measurement performance test. (a) Roll angles, and (b) Pitch angles. Legend: (--) Line y=x; (●) Observations.

(requires none or cheap measurement tools) ATV characteristics and riding parameters. Moreover, DNN generates results significantly faster than conventional modeling techniques (Bolandi et al., 2022), which is ideal for real-time prediction applications.

Table 4. Descriptive statistics for speed estimate error (m.s^{-1}).[a]

Test Velocity (m s^{-1})	Range	Average (SD)	CV (%)
2.23	0–2.72	0.77 (0.88)	114%
3.57	0–3.97	0.63 (0.97)	152%
5.36	0–4.89	0.88 (0.99)	112%
Total	0–4.89	0.75 (0.95)	126%

[a] SD = standard deviation and CV = coefficient of variation.

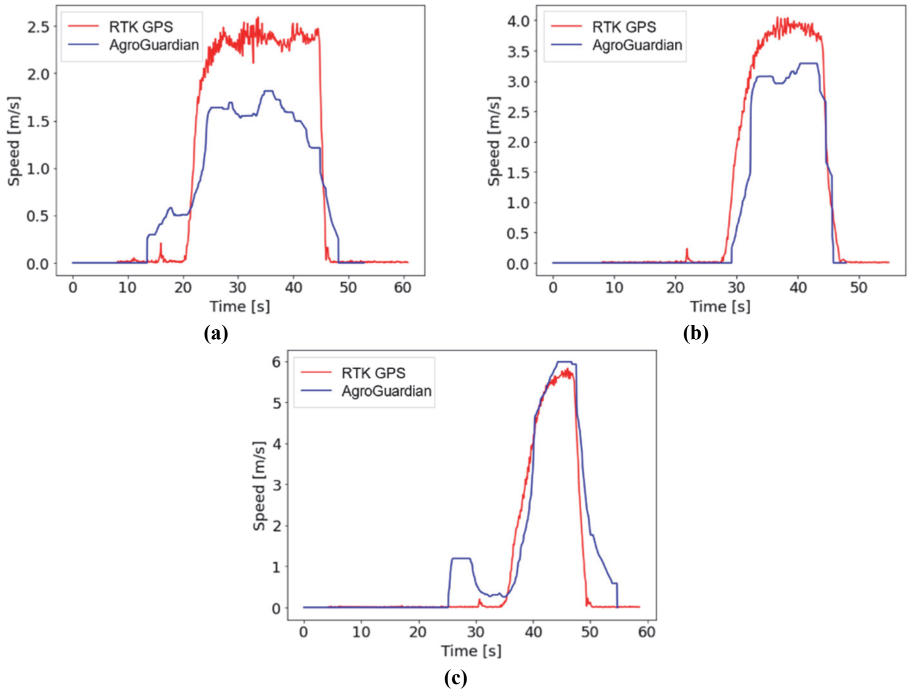


Figure 6. System's performance tests for several speeds. (a) Test at 2.23 m.s^{-1} (5 mph), (b) test at 3.57 m.s^{-1} (8 mph), and (c) test at 5.36 m.s^{-1} (12 mph).

Further, the developed system incorporates an audio-visual alert component, which is known to be a highly effective safety intervention measure (Brann et al., 2012; House et al., 2016). It alerts riders to a possible crash event, giving the rider time to take preemptive safety actions, such as speed reduction.

Research Limitations

There are a few limitations of this study that need to be considered. First, our prediction models do not account for all possible factors that may influence the risks of an ATV crash event. Terrain and weather conditions may have a direct or indirect effect on the risk of an incident. In addition, the presence of obstacles on the terrain can cause a rollover (Concannon et al., 2012; Helmkamp et al., 2011; Hicks et al., 2019; Hicks et al., 2018 Lower and Herde, 2012). Moreover, our models have not yet been validated with field tests due to safety hazards and logistical constraints. Even though the developed system was compounded by low-cost sensors, which could influence the overall accuracy of the models, the models proved to be successful in estimating the vehicle's roll and pitch angles and speed with an accuracy superior to our benchmarks.

Further, this study did not account for the rider weight shift (active riding), which can significantly affect the stability of the ATV, thus impacting the accuracy of the rollover prediction system. Active riding is promoted as a key part of ATV training and risk mitigation for rollovers. It involves the rider adjusting their body position to counterbalance the ATV's tilt and maintain stability. This riding technique was reported to increase the vehicle's lateral stability angle by up to 20% (Grzebieta et al., 2015a,b).

Conclusions

In this study, we developed and evaluated the performance of an automatic ATV crash prediction and notification device. We accessed the accuracy of four different classification algorithms, such as KNN, SVM, Random Forest, and DNN. The models used different input variables, including ride parameters (e.g., ATV speed, turning radius, and roll and pitch angles), ATV characteristics (e.g., width, length, wheelbase), and human factors (i.e., presence of a rider), accounting for a total of 51,700 samples. Overall, it was observed that the DNN model outperformed the other models with an accuracy superior to 99%. Moreover, the developed device can detect roll and pitch angles with average errors of 0.26 and 0.54 degrees, respectively, and can detect the ATV's speed with an average error of 0.75 m s^{-1}.

Although further research is required to validate it in real-world conditions, the obtained results represent an important step toward improving ATV safety.

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