# ADAS-PeVision: Advanced Driver Assistance System for Pedestrian Movement Prediction

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***Abstract*— With the advancement of autonomous vehicle innovation, precise pedestrian movement prediction has become indispensable for ensuring safe interactions between pedestrians and self-driving cars. In this research work, we propose a pedestrian tracking and prophesy framework intent at inflate pedestrian safety in densely populated environment. Our framework leverages state-of-the-art deep learning methodology, notably YOLO (You Only Look Once), for contemporaneous pedestrian detection and pursuit. By scrutinize the trajectories of detected pedestrians, we develop a prognosticative model to foretaste their future movements, thereby enabling self-driving cars to proactively adjust their etiquette to accustom pedestrian actions. To evaluate the efficacy of our approach, we conducted extensive demonstration using a diverse dataset of urban scenarios. Results demonstrate that our framework achieves high accuracy in prophesy pedestrian trajectories, with an average accuracy rate 72%. In addition to, our approach betrays robustness across various environmental circumstances such as sudden stops, direction changes, interaction with other objects in the environment and pedestrian behaviours. Overall, our research contributes to the advancement of pedestrian-aware autonomous navigation system, paving the way for safer and more methodical interactions between self-driving cars and pedestrians in urban environments. By enhancing pedestrian safety, our framework lays the footing for perceive the full potential of autonomous vehicles in transforming urban mobility and improving the quality of life for communities worldwide.**

***Keywords*— Autonomous vision. vehicles, Pedestrian safety, Pedestrian detection, Pedestrian tracking, Trajectory prediction, Deep learning, YOLO, Prognosticative modelling.***

## I. INTRODUCTION

The inauguration of autonomous cars depicts a transformative leap in transportation technology, reassuring to reshape urban mobility and revolutionize the way of travel [1]. At the heart of technology expansion lies the complex cooperation between autonomous vehicles and pedestrians, where the proficiency to accurately anticipate pedestrian movements become important for ensuring safe and efficient navigation in complex urban environments. Detecting pedestrians' next movements is a key challenge in creating self-driving cars. This involves making proactive decisions and avoiding potential dangers [2]. Autonomous vehicles can easily predict what pedestrians will be able to do in urban areas, predicting their actions in earlier stage to keep everyone safe on the road [3][4]. Even with advancements in sensor technologies, computer vision algorithms, and machine learning techniques, we can't accurately predict the pedestrian movements due to factors like occlusions, different pedestrian movements, and the ever-changing urban environments [5] [6]. These challenges require deep research and strong strategy. This research work examines how self-driving cars able to detect pedestrian movements in earlier stage as shown in Fig. 1 strongly focusing on detection, tracking, and predicting trajectories. By using computer vision, deep learning, real-time processing, and parallel processing, we aim to understand pedestrian behaviour and movements [7].

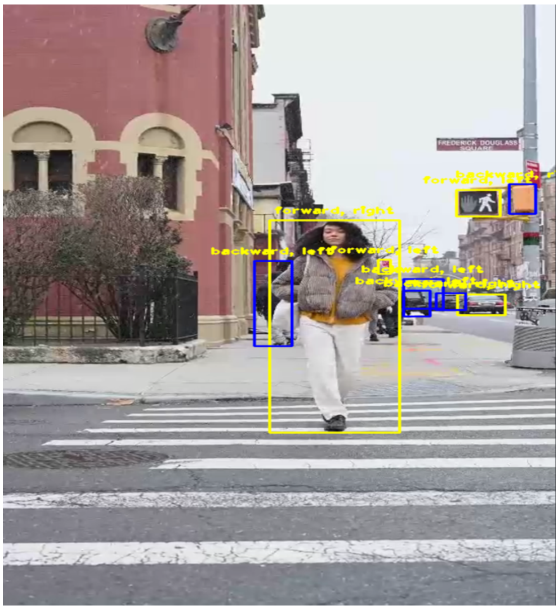


Fig. 1. Implementation of bounding boxes and future direction predictions of pedestrians

Our research work aims to achieve the following goals:

1. Methodological Exploration: We have studied various methods and technologies which is used for detecting the next movement of the pedestrians in autonomous vehicles [7]. By studying the basic principle and techniques, we aim to resolve how pedestrians are recognized and recognized in the context of autonomous cars.
2. Predictive Modelling: While exploring the detection and tracking of the pedestrian, we focus on predictive modelling to expect pedestrians' earlier movements based on their observed patterns and the surrounding cues [7], [8]. By using machine learning algorithms, we aim to reveal the time-dependent volatile of pedestrian behaviour and movement patterns.
3. Performance Evaluation: Using real-world dataset and conventional metrics, we precisely evaluate the performance of pedestrian movement prediction models [3]. By measuring the accuracy, performance evaluation such as angular error of our predictive algorithms, we aim to calculate their validity in practical sides and urban environment.
4. Implications and Applications: We explore the major implications of precise pedestrian movement prediction in strengthening the safety and efficiency of autonomous cars in urban environment. From pedestrian tracking and detection to collision avoidance systems, we explore the various applications and scenarios that could help in the advancement of pedestrian movement prediction techniques [1].

Our research work aims to improve autonomous vehicle systems to create a safe future where self-driving cars and pedestrians can safely share the road. By studying how pedestrians behave and analyse their movement, we hope to make transportation systems safer and more inclusive for everyone.

## II. LITERATURE REVIEW

Detecting pedestrians and predicting their movements earlier are essential for autonomous vehicle systems to safely handle urban areas and reduce pedestrian related accidents [7]. This research reviews current research and methods on esti mating pedestrian traffic in autonomous vehicles.
Computer vision techniques such as Haar steps and Histogra m of Oriented Gradients (HOG) have been used for pedestri an reception ( Dalal and Triggs, 2005 ). Modern deep learni ng methods such as convolutional neural networks (CNN) ar e widely used to improve the accuracy of pedestrian detectio n ( Ren et al., 2015 ). This technique allows driverless vehic les to detect pedestrians in different environments, including situations with low traffic and situations where crowds of p eople in cities are difficult to detect. can collapse and plan a safe route. Research in this area focuses on developing predi ctive models based on observing pedestrian movements and analyzing their context. Techniques such as Hidden Marko Models (HMM) and Bayesian Networks have been used to a nalyze walking behavior ( Kooij et al., 2014 ). Additionally, machine learning techniques such as convolutional neural ne tworks (RNN) and shortterm temporal (LSTM) networks ha ve been used to understand relationships in pedestrian analy sis (Alahi et al., 2016). Data and system evaluation are nece ssary to compare pedestrian detection and prediction algorit hms. Data such as KITTI ( Geiger et al., 2012 ) and City Per sons ( Zhang et al., 2017 ) provide travelers with simple bou nding boxes and trajectories from real-life urban environments. Commonly used metrics such as pr ecision, recall, mean precision (mAP), and root mean square error (RMSE) are used to calculate the results of search eng ine opinion and prediction models (Cordts et al., 2016). and future directions: Although progress has been made in travel er research and forecasting, there are still many challenges s uch as disruption to traveler experiences, changing behavior, and these need to be addressed in a timely manner**.** Future research work may focus on linking data from different sensors such as LiDAR and radar to improve the pedestrian detection accuracy and dependability (Fang et al., 2018). Improvement in machine learning algorithms, as well as consideration mechanisms and performing various operations on graphical data (Graph Neural Networks), could also help in the predictive abilities of autonomous vehicles in complex urban environment (Deo et al., 2020).

In summary, detecting pedestrian movements earlier as shown in Table. 1 is crucial for autonomous vehicles to make instantaneous decisions and avoid hazardous collisions in the urban settings[8]. Experimenters are working on developing a strong and reliable algorithm for pedestrian detection and predicting their formerly movements using computer vision, deep learning, and YOLO models, fundamentally aiming for secure and more effective self-driving cars [2].

Table. 1. FEATURES COMPARISONS OF PEDESTRIAN DETECTION SYSTEM WITH DIFFERENT SYSTEM MODEL

| **S No.** | **Key Features** | **Accuracy** | **System complexity** |
|---|---|---|---|
| Paper[1] | RPN is a fully convo lutional network that can estimate object boundaries and obje ct scores for each im age location. | 70.4% | Integrate RPN with F ast R-CNN using clustering techniques, anchor b oxes for regional rec ommendations, and multiple drop-down functions for e nd-to-end learning optimiza tion |
| Paper[2] | The initial correlatio n map was develope d using a heuristic to determine the initial HMM state probabi lity based on early G PS data. | --- | Real-time processing requi res good heuristics an d Viterbi algorithm t uning to ensure high performance without delay. |
| Paper[3] | Analyze accident-related factors, envir onmental factors, tra vel behavior and veh icle characteristics. | 70-90% | Use machine learning techniques such as ra ndom forests, gradien t boosting machines, or neural networks to identify relationships and interactions. |
| Paper[4] | State-of-the-art 2D modeling mo dels like OpenPose a nd PoseNet use deep learning techniques to accurately identif y and display import ant details in photos | 80-90% | Predicting whether a pedestrian will cross using 2D pose estimation involves analysing their body language and trajectory cues to determine their |

| | | | |
|---|---|---|---|
| | or videos to people i nstantly. | | intention of crossing the street in real-time. |
| Paper[5] | Expand vehicle dyna mics features such a s speed, acceleration , blinkers, and brake lights. | 70-90% | the model lies in the r eal- time integration of ad vanced 2D design pre diction of pedestrian behavior, prediction algorithms for traject ory prediction, multi- sensor data fusion, an d context- aware decision makin g. |

## III. SYSTEM MODEL

In a research effort to improve pedestrian prediction while d riving, we present a new method that leverages the power of the YOLOv8 model Fig. 2 with video input [9].
The YOLOv8 model forms the basis of our approach, provi ding passengers with the ability to effectively and accurately identify passengers necessary to ensure safety in a safe envi ronment. uniformity and consistency. This involves correcti ng the frame size of the resolution model 224, 224 to help i mprove the performance of the next model. By generating in put data, we reduce the difference between image scale and contrast, thus increasing the power and reliability of the rov er's prediction. in case. Leveraging object detection capabilit ies, YOLOv8 can accurately identify passengers and place t hem in sealed containers. These boxes act as beacons indicat ing travelers' current and desired location, making predictio ns about their next move. We assign custom colors to bound ing boxes based on the estimated direction of pedestrian mo vement. For example, a yellow box indicates that the pedestr ian is moving towards the vehicle, while other colors indicat e that the pedestrian is moving away from the vehicle. This visual impairment increases awareness of the nature of the d riving impairment and aids in decision making
[7]. Our system, which constantly monitors pedestrians and traffic, can instantly detect situations where pedestrians may interact with traffic. In this case, the system distributes erro r messages to alert the autonomous driving system so that it can intervene in time to prevent accidents and ensure the saf ety of pedestrians. Measurement tool
[1]. The basis of our evaluation is the calculation of the ang ular error of the actual and estimated pedestrian position. Th is measurement provides information about the accuracy an d precision of our forecast models, allowing us to refine and improve their performance. accuracy and generalization abi lity. Through extensive testing and analysis, we constantly i mprove the design and training process, trying to achieve th e best performance in different situations around the world. Self-driving cars
[5]. By coordinating the software with onboard sensors and control systems, we ensure seamless operation and instant re sponse, thus enabling safe and efficient autonomous navigat ion in a passenger-
rich environment. Predictive pedestrians support self- driving by combining deep learning technology, advanced v ision systems and safety features. Using the YOLOv8 standa rd and innovative design, we aim to improve the reliability, safety and performance of autonomous driving, ultimately p roviding greater transportation safety and availability [7].

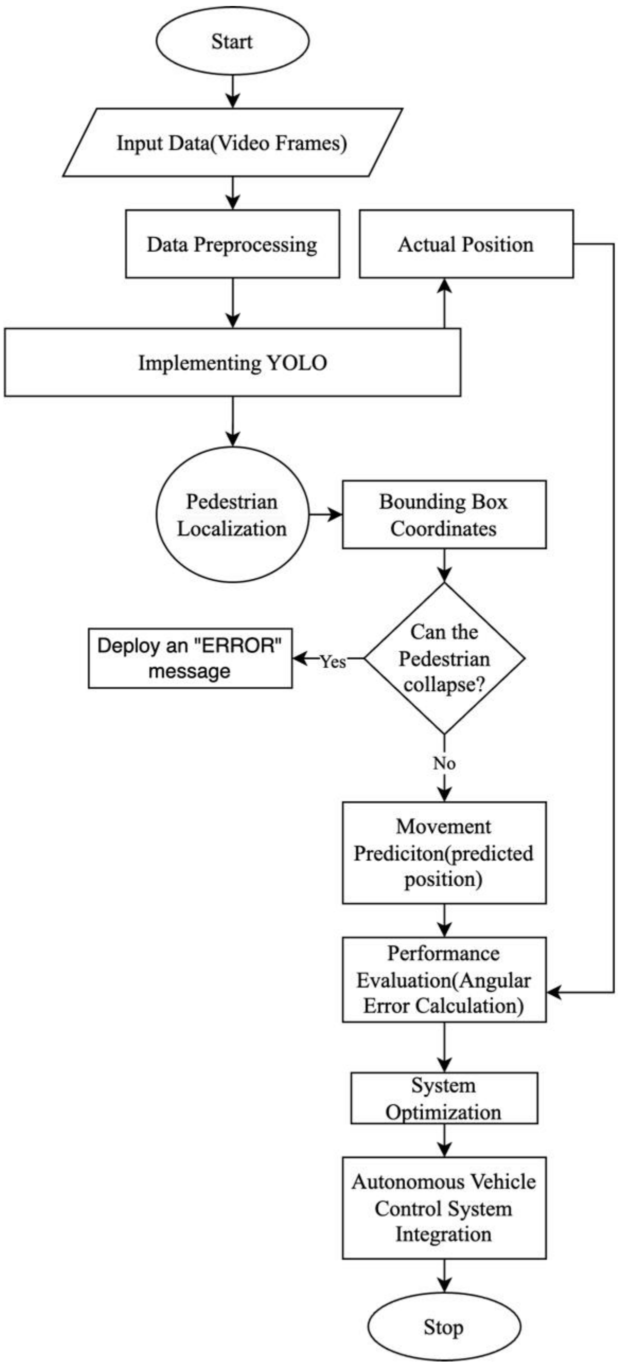


Fig. 2. Diagram to show the various layers in the System Model(flowchart)

## IV. WORKING

YOLO (You only look as soon as), introduces a sophisticated architecture to address the challenges trendy correct and efficient item detection in pics. This model stands at the vanguard cutting-edge computer vision studies, supplying overall performance in real-time item detection obligations[9].

### A. Model Architecture

- Spine: YOLOv8 contains a deep convolutional neural network (CNN) as its spine, meticulously designed for robust characteristic extraction from enter images. Drawing concept from the Darknet structure, this spine community incorporates more than one convolutional layer, permitting the model to seize complex info and abstract functions crucial for object detection [3].
- Feature Pyramid: To seize gadgets state-of-the-art varying sizes and scales, YOLOv8 integrates a characteristic pyramid network (FPN) or comparable mechanism. This revolutionary method leverages multi-scale functions extracted from one-of-a-kind tiers trendy abstraction inside the network, making sure comprehensive coverage ultra-modern gadgets throughout the picture.
- Detection Head: on the core modern day YOLOv8 lies its detection head, a chain latest convolutional layers devoted to predicting bounding boxes, magnificence chances, and confidence rankings. with the aid of analysing capabilities at more than one scales and utilizing anchor packing containers, this component allows correct localization and classification state-of-the-art objects, enhancing the model's precision and reliability.
- Loss characteristic: at some point of education, YOLOv8 optimizes a combination contemporary loss feature, together with localization loss (e.g., clean L1 loss) and class loss (e.g., pass-entropy loss). these loss capabilities are carefully calibrated to minimize the disparity among expected and ground-reality bounding packing containers and sophistication labels, fostering continuous improvement in model performance.
- Submit-Processing: Following inference, YOLOv8 employs submit-processing techniques along with non-maximum suppression (NMS) to refine the detected bounding packing containers and eliminate redundant detections. NMS ensures that each object is represented via a unmarried bounding container with excessive self-assurance, streamlining subsequent analysis and selection-making techniques.
- Output: The end result today's YOLOv8's computational prowess is a comprehensive output comprising specific bounding packing containers and associated class probabilities. This output now not only indicates the presence and region modern-day gadgets within the input image however also serves as a testimony to the version's efficacy and flexibility throughout diverse applications in computer vision and past.

With its unheard-of overall performance, YOLOv8 continues to push the bounds present day object detection, empowering researchers, builders, and practitioners to liberate new possibilities in fields including self-sufficient using, surveillance, and augmented fact.

### B. Model Operation:

In our quest to enhance pedestrian prediction for using situations, we gift a pioneering technique that harnesses the electricity of the YOLOv8 version alongside video enter [10]. Serving because the backbone of our approach, YOLOv8 gives sturdy pedestrian detection talents crucial for ensuring safety in dynamic using environments. Our method commences with pre-processing the video enter, ensuring uniformity by using standardizing the body length to a decision of 224x224. This pre-processing step ambitions to mitigate variations in picture scale and comparison, thereby bolstering the reliability and resilience of our pedestrian prediction system [3]. Capitalizing on YOLOv8's item detection prowess, our gadget accurately identifies pedestrians and encloses them inside bounding packing containers. these bounding packing containers act as markers of pedestrians' contemporary positions and expected actions, facilitating predictions regarding their future trajectories as shown in Fig. 3 .

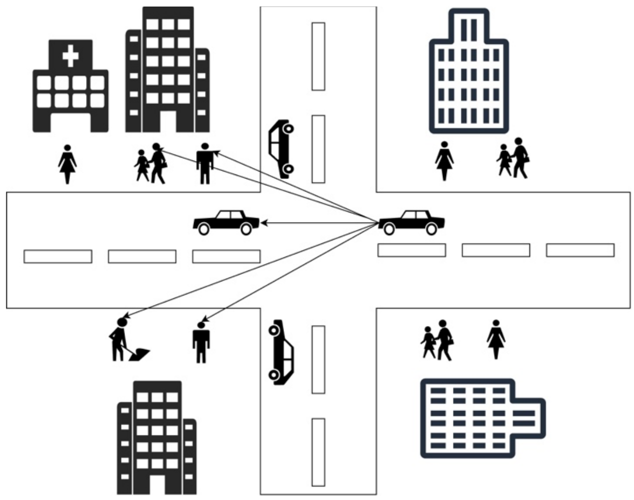

Fig. 3. Depicting ADAS in self-driving cars

To decorate interpretability and situational recognition, we personalize the colours of the bounding bins based totally on the perceived direction of pedestrian movement [8]. as an example, a yellow bounding box signifies pedestrian movement in the direction of the automobile, at the same time as different shades denote movement far away from it. Furthermore, our system constantly video display unit’s pedestrian and traffic dynamics, unexpectedly detecting capability collision dangers [11]. In such instances, the device right away dispatches mistakes messages to alert the self-sufficient driving device, allowing timely intervention to avert accidents and shield pedestrian well-being [8]. Our assessment approach revolves around computing the angular mistakes between actual and expected pedestrian positions. The maximum deviation of the predicted and actual position of the pedestrian predicted by the model could be 180° i.e. that is completely opposite to the actual position.

This metric furnishes insights into the accuracy and precision of our prediction models, guiding iterative refinement efforts to beautify performance and flexibility throughout numerous actual-global scenarios encountered in independent using contexts [12]. Also, the model has been predicted the dot trajectories of each pedestrian detected in the dataset, from the starting to the ending position as shown in Fig. 4.

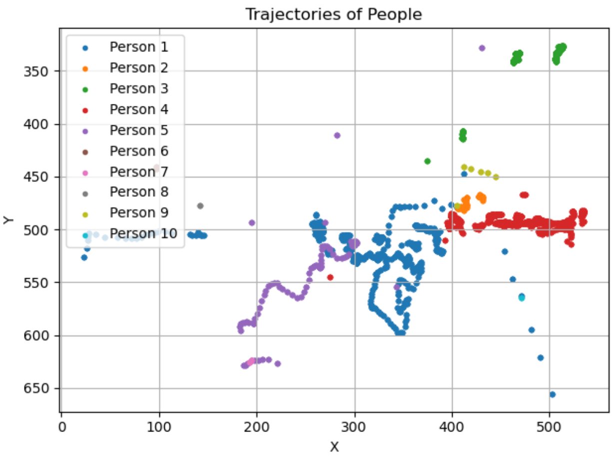


Fig. 4. Trajectory prediction of pedestrians

Through rigorous checking out and evaluation, we always excellent-track the layout and training processes of our pedestrian detection gadget as shown in Fig. 5, striving to achieve peak performance in numerous operational environments by means of seamlessly integrating our device with onboard sensors and control structures of self-using cars, we make sure seamless operation and instant responsiveness, fostering secure and efficient navigation in pedestrian-dense settings. In essence, our pedestrian detection gadget harnesses technology, state-of-the-art imaginative and prescient structures, and proactive protection measures to raise the reliability, protection, and efficacy of self-sustaining riding. with the aid of leveraging the talents of the YOLOv8 version and innovative layout techniques, we goal to bring in a generation of more desirable transportation protection and accessibility in self-sustaining driving nation-states.

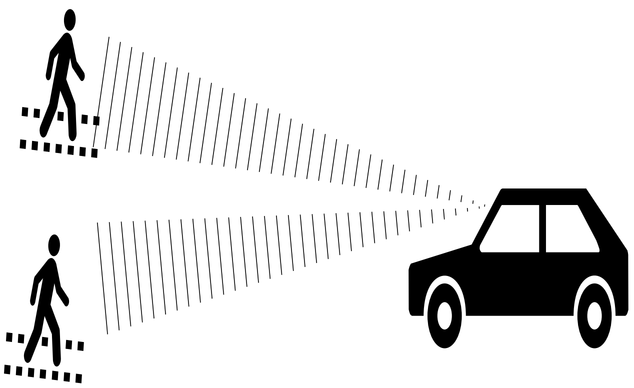

Fig. 5. Pedestrian detection by working cameras

### C. *Model Formulas*

1.Smoothen Angles Function:

This formula given at Equation 1 computes the smoothen angle at index *I* by taking the mean of the angles within a window centred at *i*. The window size is specified by the parameter '*window size*'.

$$smoothed\_angle_i = \frac{1}{window\_size} \sum_{j=i-\frac{window\_size}{2}}^{i+\frac{window\_size}{2}} angles_j \qquad (1)$$

2.Centroid Calculation:

These formulas given at Equation 2calculate the centroid coordinates of a bounding box given its top-left corner *(x1, y1) (x1, y1)* and bottom-right corner *(x2, y2) (x2, y2)*.

$$centroid_x = \frac{x1+x2}{2}, centroid_y = \frac{y1+y2}{2} \qquad (2)$$

3.Angle Calculation:

This formula at Equation 3 calculates the angle between two points $(x1, y1)$ $(x1, y1)$ and $(x2, y2)$ $(x2, y2)$ using the arctangent function atan2. It represents the direction of movement from the previous position to the current position.

$$angle = atan2(y_2 - y_1,\ x_2 - x_1) \qquad (3)$$

4.Average Angular Error Calculation:

This formula at Equation 4 calculates the average angular error in degrees by taking the mean of the smoothed angles and converting radians to degrees $(\frac{180}{\pi})$.

$$average_{error_{degrees}} = \frac{1}{N} \sum_{i=1}^{N} smoothed_{angles_i} \times \frac{180}{\pi} \qquad (4)$$

## V. RESULT AND DISCUSSION

Our pedestrian detection system exhibited different accuracies across different pedestrian density scenarios. In the low pedestrian density scenario, the system got an accuracy rate of 69.084%, with an error rate of 30.915%. Moving towards the moderate pedestrian density scenario, the accuracy improves to 70.795%, with an error rate of 29.204%. Overall, the dataset with the highest density scenario, the system demonstrated the highest accuracy of 78.490%, accompanied by an error rate of 21.509%.

On an average, our system achieved an accuracy rate of 72.789% with an error rate of 27.209% across all pedestrian density scenarios. The observed trend of increasing accuracy with higher pedestrian scenarios underscores the adaptability and robustness of our pedestrian prediction system. As pedestrian density escalates, the systems performance experiences enhancement, resulting in elevated accuracies and diminished error rates.

This trend can be attributed to the distinctive behavioural patterns of pedestrians across varying density environments. In low pedestrian density scenarios, the sporadic nature of pedestrian presence poses challenges for detection. Conversely, in high pedestrian density scenarios, the system benefits from increased visual cues and clearer pedestrian delineation, leading to superior detection performance.

The highest accuracy achieved in the high pedestrian density scenario underscores the system's proficiency in identifying pedestrians amidst crowded environments, contributing to enhanced pedestrian safety and bolstering the advancement of autonomous driving technologies.