Conceptual Design of an Autonomous Vehicle for Road Anomaly Detection and Manoeuvring

Jibril A. Bala
Department of Mechatronics Engineering,
Federal University of Technology, Minna
Minna, Nigeria
jibril.bala@futminna.edu.ng

Steve A. Adeshina
Department of Electrical and Electronics Engineering,
Nile University of Nigeria
Abuja, Nigeria
steve.adeshina@nileuniversity.edu.ng

Abiodun M. Aibinu
Department of Mechatronics Engineering,
Federal University of Technology, Minna
Minna, Nigeria
abiodun.aibinu@futminna.edu.ng

***Abstract* – The decaying road infrastructure in Nigeria raises the need for autonomous vehicles capable of detecting and navigating road anomalies. Existing control schemes for navigation are unsuitable for implementation due to the unstructured and dynamic nature of the environment. Due to the aforementioned factors, this paper presents a conceptual design of an autonomous vehicle for road anomaly detection and navigation. The vehicle utilizes a computer vision scheme based on Convolutional Neural Networks (CNN) for road anomaly detection and Model Predictive Control (MPC) for manoeuvring. The implementation of a vehicle prototype with remote monitoring and control capabilities is also presented in this paper. The implementation of this will provide an efficient scheme for road anomaly detection and manoeuvring in autonomous vehicles.**

***Index Terms* –Autonomous Vehicles, Computer Vision, Model Predictive Control, Road Anomaly Detection, Vehicle Navigation**

I. Introduction

An AV, also known as a self-diving or driverless vehicle, is a vehicle that can work with little or no driver input [1]. Such vehicles are able to perceive their environment through sensors and act accordingly through a range of operations such as acceleration, braking and steering [1], [2]. AVs have the potential to reduce human error, alleviate congestion, and increase productivity [3]. AV research and development has increased significantly over the past decade [4]. Companies like Google, Tesla, and Uber have applied to AV innovations [2], [3]. This significant progress has contributed to commercial applications facing the AV industry through conceptual design, extensive testing, and technological development. However, as human errors contribute to several traffic accidents, the minimisation of the human factor would improve vehicle safety and decrease road accidents [1]. In addition, the design of AVs has become a requirement due to the rapid advancement and applications of information and communication technology to cater for an aging population [5].

The dilapidated condition of majority of the roads in Nigeria has caused a significant economic setback [6]. Due to geographical factors, such as rainfall and erosion, and poor construction, the road network in Nigeria is afflicted by potholes, swelling and stripping [6]. In addition, the indiscriminate erection of speedbumps without approval, labels, and adherence to the height and width standards has plagued most of the roads in Nigeria [7], [8]. The presence of these road abnormalities results in crashes which leads to damage to the vehicle, destruction of property, additional mutilation to the road, and loss of lives [7]–[9]. This situation increases the financial burden on the populace and the government. AVs have the potential of significantly reducing the rate of road fatalities on decaying and damaged due to their capability of identifying road anomalies and manoeuvring around them.

Existing works in road anomaly detection and manoeuvring schemes have salient limitations which include unsuitability for dynamic and outdoor environments [10]–[13], lack of consideration of vehicle speed during navigation [14]–[16], lack of consideration of nonlinearities and disturbances [10]–[13], [14]–[16], absence of suitable control schemes for navigation [8], [17], [18], [19], [20], [21], and the absence of a remote monitoring and control feature. In addition, majority of the detection techniques reviewed suffer from lack of an intelligent technique and absence of previous road data in the implementation.

Instances of control algorithms implemented in vehicle navigation include classical control algorithms, robust control schemes, Sliding Mode Control (SMC), Fuzzy Logic Control (FLC), and Model Predictive Control (MPC) [22]. However, some of these techniques (such as FLC and SMC) deal with worst-case disturbances which result in 'too conservative' performances. In addition, feedback control schemes are usually unable to predict future occurrences due to their reliability on current system states [23]. Additionally, SMC suffers from chattering effect which are high frequency oscillations around the sliding surface [24]. The classical PID control scheme does not perform satisfactorily in dynamic environments due to the constant gain characteristic. Furthermore, fuzzy logic requires experience or experimental data for accurate performance, which may not always be available [25]. Thus, the need arises for an effective control scheme able to anticipate future occurrences and possess suitable disturbance rejection capabilities for effective autonomous vehicle navigation

This paper presents a conceptual design of an autonomous vehicle for road anomaly detection and manoeuvring. The development of an autonomous vehicle for navigation in unstructured environments using MPC and Convolutional Neural Networks (CNN) based computer vision techniques is proposed. The AV will be capable of detecting ridges (bumps) and depressions (potholes) using computer vision and machine learning techniques. In addition, the vehicle will use NMPC to navigate around the identified road anomalies by

978-1-6654-3493-5/21/$31.00 ©2021 IEEE

controlling the position and velocity of the vehicle. Furthermore, the AV will provide real time monitoring and control capabilities via a mobile application using Internet of Things (IoT).

The remainder of this paper is divided into four (4) sections. Section II provides a detailed description of the CNN-based computer vision technique while Section III presents a description of the MPC algorithm. Section IV provides information on the prototype development while the conclusion is presented in Section V.

II. CNN-BASED COMPUTER VISION ALGORITHM

The detection of smooth roads, road lanes, potholes, and bumps will be carried out using a Computer Vision model based on Convolutional Neural Networks (CNN). The features of the acquired images will be extracted using computer vision techniques and then the features will be fed into the CNN model for classification and road anomaly detection.

The steps involved in the Computer Vison pipeline are shown in Figure 1 and elucidated subsequently.

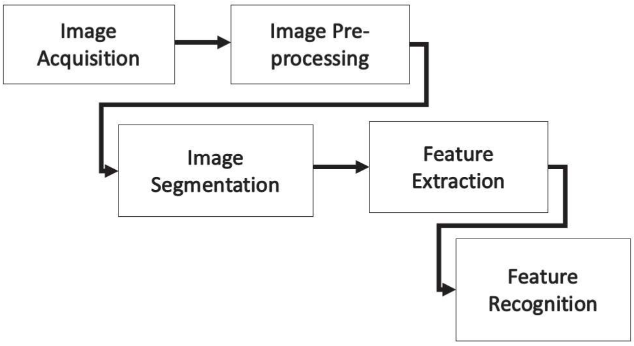

Figure 1: Computer Vision Pipeline

a. **Image Acquisition:** This involves acquiring the visual feed and images from the camera. The raspberry pi V2 camera is being envisaged as the prospective image acquisition device. This choice is based on the features of the camera which include its ability to take still images of a resolution of 3280x2464 (8MP) or record 4K video at a frame rate of 30 frames per second (FPS). The video feed coming in to the microcontroller will be evaluated frame by frame. The processing power of the raspberry pi controller board will be capable of handling the frame rate of the video feed.

b. **Image Pre-processing:** After the acquisition of the images, the images need to be pre-processed before further processing. The image acquired in step (a) is in the Red-Green-Blue (RGB) format. The first step will be colour space conversion, in which the image will be converted from an RGB colour format to grayscale. Equation 1 shows the conversion process from RGB to grayscale.

$$\mathrm{I}_{\mathrm{grayscale}} = 0.3\mathrm{R} + 0.59\mathrm{G} + 0.11\mathrm{B} \qquad (1)$$

Where R, G, and B represent the values of the red, green, and blue channels respectively.

After the colour space conversion, the image will be filtered to remove noise and other unwanted features. This process will be achieved using an N-dimensional convolution filter. The convolution process is described by equation 2.

$$Y(i_1, i_2, \ldots \ldots i_n) = \sum_{k_1} \sum_{k_2} \ldots \ldots \sum_{k_n} X_1(k_1, k_2, \ldots \ldots k_n) X_2(i_1 - k_1, i_2 - k_2, \ldots \ldots \ldots i_n - k_n) \qquad (2)$$

Where *Y*, X_1, and X_2 represent the N-dimensional variables. Equation 2 can be simplified as shown in equation 3.

$$g(x, y) = \omega * I_{grayscale} \qquad (3)$$

Where g(x,y) is the filtered image, ω is the convolutional filter kernel, and $\mathrm{I}_{\mathrm{grayscale}}$ is the grayscale image obtained in step (b).

When the filtering is concluded, the next task to be carried out is image enhancement. This process will be achieved using contrast limited adaptive histogram equalisation (CLAHE). CLAHE is useful for contrast enhancement in images and instead of computing one histogram for the entire image, the algorithm computes multiple histograms and redistributes the lightness value of the image. Unlike regular adaptive histogram equalisation which amplifies noise in homogenous regions of an mage, CLAHE avoids this phenomenon by limiting the amplification effect [26].

c. **Image Segmentation:** The pre-processed grayscale image will be converted to an intensity image using adaptive thresholding techniques and the image will be divided into different parts (segmented) using edge detection techniques. Adaptive thresholding has an advantage over fixed thresholding in the sense that adaptive thresholding computes different threshold for various regions of the image. In this research, the Gaussian adaptive threshold method will be used which computes weighted sum of neighbourhood values and the weights are a Gaussian window. For the edge detection task, the Sobel edge detection algorithm will be used. This technique used gradient magnitude and performs better than the Canny edge detection technique which suffers from high sensitivity and noise.

d. **Feature Extraction:** The extraction of relevant features from the segmented image will be achieved using Fourier Descriptors method. This technique utilises Discrete Fourier Transforms (DFT) to describe the shapes of images by transforming a given image to a representation in the frequency domain [27]. The process of DFT in images processing is presented in equation 4.

$$f(n, m) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} g_s(x, y) e^{-i2\pi\left(\frac{ni}{N} + \frac{mj}{N}\right)} \qquad (4)$$

Where *f(n,m)* is the image in the Fourier domain, $g_s(x,y)$ is the segmented image in the spatial domain obtained from step (c), N is the square size of the input image, The Fourier Descriptor technique is a widely used method in shape description applications due to its ability in representing image shapes using numerical values and its invariance in terms of rotation, translation, and scale [27].

e. **Feature Recognition:** The feature recognition will be carried out using Convolutional Neural Networks. The numerical values obtained from the Fourier descriptor will be passed into the CNN model for training, testing, validation, and classification.

The classification of extracted features will be achieved using Convolutional Neural Networks (CNN). CNN is a class of deep neural networks widely used in visual recognition. The neurons in CNN are fully connected and are connected in complex patterns. A diagram of a CNN model is presented in Figure 2.

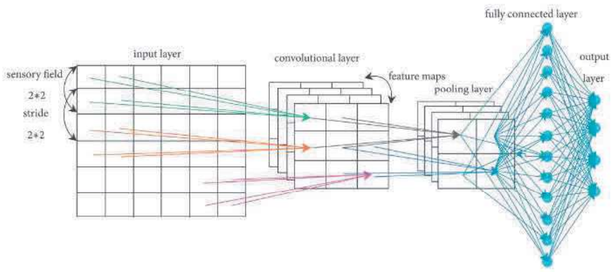

Figure 2: Architecture of Convolutional Neural Networks [28].

The CNN model will be implemented using a 70-15-15 format. This implies that 70% of the data will be used for training the model, 15% will be used for testing, and 15% will be used for validation.

Two types of data will be used which will be acquired from two sources. In the first set of data, the image dataset will be obtained from online data repositories such as Kaggle. These images will be obtained in three categories, namely: images of roads with speedbumps, images of roads with potholes, and images of roads without anomalies. The Kaggle dataset will also be augmented with camera images of deficiencies in some selected Nigerian roads which will serve as the second set of data. These images will be obtained with a high-resolution camera and will be acquired to increase the variability and volume of the dataset.

The features of the obtained images will be extracted to form a numerical dataset suitable for the CNN. After the model has been developed, it will be deployed to the controller for implementation on the AV.

III. VEHILCE MODEL AND MPC SCHEME FOR NAVIGATION

After identifying road anomalies using the CNN-based computer vision technique, the vehicle needs to be manoeuvred in appropriate direction to avoid the detected faults on the road. A Model Predictive Control (MPC) scheme is envisaged as the prospective control technique. However, to implement the MPC scheme, the vehicle needs to be modelled to represent its dynamics, both longitudinal and lateral. The vehicle dynamics will be modelled based on the longitudinal and lateral forces acting on the vehicle shown in Figure 3.

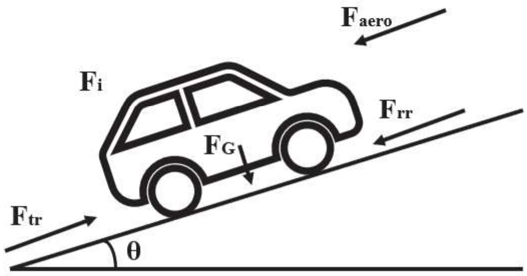

Figure 3: Longitudinal Vehicle Dynamics

The diagram shown in Figure 3 highlights the forces considered when modelling the longitudinal dynamics of a vehicle. F_{tr}, F_{aero}, F_{rr}, F_g, and F_i represent the tractive force, aerodynamic drag force, rolling resistive force, grade force, and inertial force, respectively. For the vehicle to move forward, the tractive force must overcome all the resistive forces [29]. This rule is shown in equation 5.

$$F_{tr} = F_{aero} + F_i + F_{drag} + F_g \tag{5}$$

The rolling resistive force, F_{rr} is a product of the vehicle mass, m, gravity, g, and the rolling resistive coefficient, C_{rr}.

$$F_{rr} = mgC_{rr} \tag{6}$$

The aerodynamic drag force is calculated as shown in equation 7.

$$F_{aero} = \frac{1}{2}\rho C_d A_f V^2 \tag{7}$$

The variables ρ, C_d, A_f, and V represent the air density, drag coefficient, vehicle frontal area, and vehicle velocity, respectively. The grade force and inertial force are obtained as shown in equations 8 and 9, respectively.

$$F_g = mgsin(\theta) \tag{8}$$

$$F_i = \alpha m_i \tag{9}$$

The parameters θ, α, and m_i respectively represent the road angle, vehicle acceleration, and vehicle inertial mass.

For the lateral dynamics of the vehicle, Figure 4 shows the lateral forces acting on the vehicle. Modelling of the lateral dynamics of the vehicle involves representation of the variables that are responsible for the sideways motion of the vehicle. These parameters include lateral displacement, yaw, yaw rate, lateral displacement, and lateral acceleration.

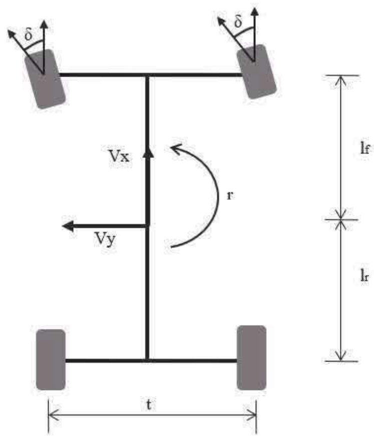

Figure 4: Lateral Dynamics of the Vehicle

In Figure 4, δ is the steering angle, t is the vehicle track width, Vx is the longitudinal velocity of the vehicle, Vy is the lateral velocity of the vehicle, and r is the vehicle yaw. The parameters lf and lr respectively represent the front wheel base and the rear wheel base.

A force balance equation can be obtained for the longitudinal and lateral forces acting on the vehicle, and a torque balance equation can also be obtained for the torque around the vertical axis of the vehicle. Equations 10, 11, and 12 respectively show the longitudinal force balance, the lateral force balance, and the torque balance equations.

$$ma_x = (F_{xfl} + F_{xfr})cos\delta - (F_{yfl} + F_{yfr})sin\delta + F_{xrl} + F_{xrr} - F_{aero} \quad (10)$$

$$ma_y = (F_{xfl} + F_{xfr})sin\delta + (F_{yfl} + F_{yfr})cos\delta + F_{yrl} + F_{yrr} \quad (11)$$

$$J_z\dot{r} = l_f(F_{xfl} + F_{xfr})sin\delta + l_f(F_{yfl} + F_{yfr})cos\delta - l_r(F_{yrl} + F_{yrr}) - \frac{t}{2}(F_{xfl} + F_{xfr})cos\delta + \frac{t}{2}(F_{yfl} + F_{yfr})sin\delta - \frac{t}{2}(F_{xrl} - F_{xrr})$$

(12) [30], [31]

In equations 9, 10, and 11, the variables F_{xfl}, F_{xfr}, F_{xrl}, and F_{xrr} respectively signify the longitudinal forces for the front left, front right, rear left, rear right wheels. The parameters F_{yfl}, F_{yfr}, F_{yrl}, and F_{yrr} represent the lateral forces for the front left, front right, rear left, and rear right wheels respectively.

Using the vehicle model, the MPC scheme will steer the car in the required direction to avoid road anomalies. MPC is a model-based control technique and is an extension of optimal control. The main concept of MPC is to use the system model to predict and anticipate future states of the system [25]. MPC has the ability to deal with multiple inputs and states of a system and also minimise a cost function consisting of the states and inputs [32]. MPC has been widely used in recent years for various applications due to its ability to handle complex dynamics and predict future occurrences under a set of operation constraints [33], [34]. Due to the algorithm's ability to handle constraint on state variables and control inputs, whilst achieving multi-objective optimisation [23], MPC has exhibited good control effect and high control accuracy especially in trajectory control of AVs [25].

The MPC algorithm attempts to predict future outputs at every step, k for a certain prediction horizon, n. The algorithm optimises a cost function, and applies a corresponding control input, u. The process is repeated when a new measurement or input is detected. The standard MPC cost function is given in equation 13.

$$J(n) = \sum_{i=k+1}^{k+n}\left(x_d(i) - x(i)\right)^T Q\left(x_d(i) - x(i)\right) + \sum_{i=k}^{k+n-1}\left(u(i) - u(i-1)\right)^T R\left(u(i) - u(i-1)\right) \quad (13)$$

Here, x_d is the set point, and Q and R are appropriate weight matrices. However, the MPC cost function given in equation 13 will be modified to cater for the appropriate parameters which are the presence/absence of bumps and potholes, the road lanes, and obstacles detected.

IV. AV PROTOTYPE DEVELOPMENT

A model car would be used for the prototype development of the system. The car will be modified by incorporating sensors and actuators to provide the required features of the AV. The car will be fitted with a camera connected to a controller running the CNN-based computer vision algorithm for road anomaly detection. The controller will also run the MPC algorithm for vehicle manoeuvring.

The AV would be powered by a 12V DC battery to provide power to the controller board, sensors, and actuators. The system will be controlled by a Raspberry Pi 4 microcontroller board, which serves as the hub of the system. The microcontroller board was selected based on its features such as a 64-bit ARMv8-A instruction set, a 1.6 GHz CPU, a 1 GB memory, and inbuilt Wi-Fi module. The instruction set, memory, and processing speed will ensure fast processing power and handle computational complexities, while the on board Wi-Fi module will provide internet access for remote monitoring and control.

The inputs to the microcontroller are the signals from the ultrasonic sensors, co-ordinates from the GPS module, and visual feed from the camera. The ultrasonic sensor will be used to detect obstacles along the vehicle's path, which in turn will aid the vehicle avoid barriers and collision. The GPS module will provide location information to the microcontroller for monitoring purposes. The camera, which acts as the major perception unit of the microcontroller, will be used to detect ridges, potholes, and road lanes to avoid steering off the road. The running on the microcontroller will be three major algorithms which are the Nonlinear MPC scheme, the CNN model, and the road anomaly detection algorithm. The outputs of the microcontroller will be the steering and velocity signals sent for actuation. These signals will control the position and speed of the vehicle for effective manoeuvring around potholes and bumps. A block diagram representing the interactions between the microcontroller and various components is shown in Figure 5.

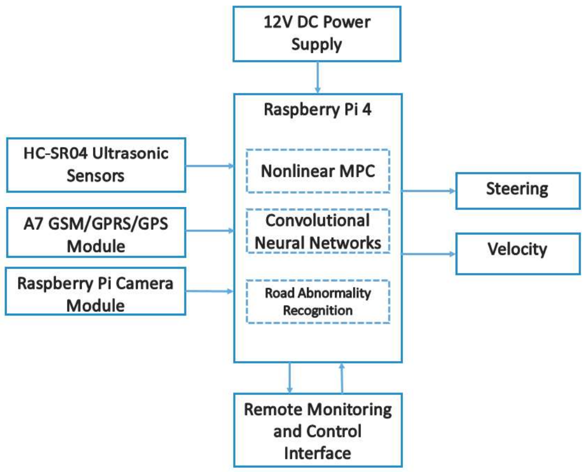

Figure 5: Prototype System Architecture

A mobile application will be developed for monitoring and control of the AV from a remote location. The Remote Monitoring and Control interface shown in Figure 6 will be developed using principles of Internet of Things (IoT). The microcontroller will transmit data obtained from sensors via a Wi-Fi module to a dedicated mobile application for monitoring. Additionally, the mobile application will have the capability of sending signals to the microcontroller via the Wi-Fi module. These signals will be interpreted by the controller in order to execute actuator movement.

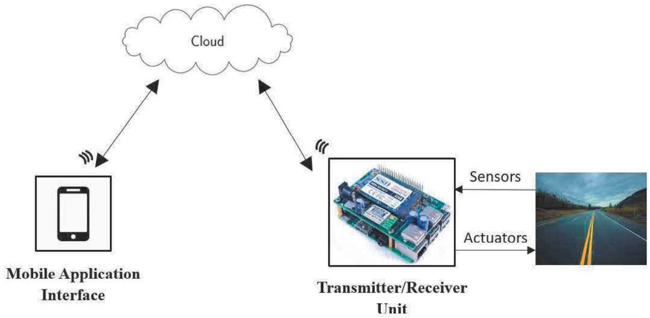

Figure 6: Overview of Remote Monitoring and Control Interface

The mobile application will be developed using Dart programming language and android studio. The application will have specific features such as viewing the camera feed of the AV, notification pothole and speedbump detection, starting and stopping the AV, and monitoring the GPS co-ordinates of the AV.

V. CONCLUSION

This paper introduces a conceptual design for a road anomaly detection and manoeuvring scheme in AVs. The device contributes to the improvement of AV perception by its ability to detect depressions and bumps using computer vision and machine learning technology. Furthermore, the ability of the AV to manoeuvre through road anomalies can increase car and driver safety in areas affected by these phenomena. The use of MPC provides predictive features and optimum efficiency in AV manoeuvring, resulting in a technique for ridge and pothole identification using a method that is not extensively studied due to computational complexities. Furthermore, the vehicle will be able to provide remote monitoring and control features via a mobile device. This feature will be useful for surveillance in remote and inaccessible areas, search and rescue operations, and delivery purposes. Generally, the implementation and adoption of this system will provide a means for the reduction of road crashes and provide a technique for exploration of inaccessible areas.

ACKNOWLEDGEMENT

The authors wish to acknowledge Tertiary Education Trust Fund (TETFUND), Nigeria for funding this research under the project titled ‘Novel Road Accident Monitoring and Prevention System for Nigerian Roads and Highways’ (NRF/SETI/TRT/00035) under the 2020 National Research Fund (NRF) grant cycle.

REFERENCES

[1] I. Barabás, A. Todoruţ, N. Cordoş, and A. Molea, “Current challenges in autonomous driving,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 252, no. 2017, pp. 1–6, 2017.

[2] Q. Pham, “Autonomous vehicles and their impact on road transportation,” JAMK University of Applied Sciences, 2018.

[3] S. Pendleton *et al.*, “Perception, Planning, Control, and Coordination for Autonomous Vehicles,” *Machines*, vol. 5, no. 6, pp. 1–54, 2017.

[4] S. J. Babak, S. A. Hussain, B. Karakas, and S. Cetin, “Control of autonomous ground vehicles: A brief technical review,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 224, no. 2017, pp. 1–6, 2017.

[5] S. A. Bagloee, M. Tavana, M. Asadi, and T. Oliver, “Autonomous vehicles: challenges, opportunities, and future implications for transportation policies,” *J. Mod. Transp.*, vol. 24, no. 4, pp. 284–303, 2016.

[6] H. Wazoh, S. Daku, and F. G. Samuel, “Investigative Study Of Possible Causes Of Failure Of A Section Of Road In Jos- Plateau , North - Central Nigeria,” *J. Multidiscip. Eng. Sci. Stud.*, vol. 2, no. 11, pp. 1128–1132, 2016.

[7] A. E. Moses and A. A. Fortunatus, “The Use of GIS in the Spatial Distribution of Speed Bumps within Afikpo,” *J. Geogr. Environ. Earth Sci.*, vol. 12, no. 1, pp. 1–7, 2017.

[8] J. M. Celaya-padilla *et al.*, “Speed Bump Detection Using Accelerometric,” *Sensors*, vol. 18, pp. 1–13, 2018.

[9] G. C. Enwerem and G. A. Ali, “Economic Effects of Bad Roads on Vehicle Maintenance in Nigeria,” *Int. J. Sci. Res. Publ.*, vol. 6, no. 6, pp. 761–766, 2016.

[10] S. Rahman, S. Ullah, and S. Ullah, “Obstacle Detection in Indoor Environment for Visually Impaired Using Mobile Camera,” *J. Phys. Conf. Ser.*, vol. 960, no. 1, pp. 0–7, 2018.

[11] Y. Zhu, B. Yi, and T. Guo, “A Simple Outdoor Environment Obstacle Detection Method Based on Information Fusion of Depth and Infrared,” *J. Robot.*, vol. 2016, pp. 1–10, 2016.

[12] K. Vasavi and M. V. S. Praveen, “Obstacle Detection and Avoidance Autonomous Car,” *Int. J. Eng. Trends Technol.*, vol. 9, no. 15, pp. 783–790, 2014.

[13] D. Xie, Y. Xu, and R. Wang, “Obstacle detection and tracking method for autonomous vehicle based on three-dimensional LiDAR,” *Int. J. Adv. Robot. Syst.*, vol. 2019, pp. 1–13, 2019.

[14] L. Bascetta, G. Ferretti, M. Matteucci, and M. Bossi, “LFT-based MPC Control of an Autonomous Vehicle,” *IFAC-PapersOnLine*, vol. 49, no. 15, pp. 7–12, 2016.

[15] F. Borrelli, P. Falcone, T. Keviczky, J. Asgari, and D. Hrovat, “MPC-based approach to active steering for autonomous vehicle systems,” *Int. J. Veh. Auton. Syst.*, vol. 3, no. 2, pp. 265–291, 2005.

[16] P. Falcone, H. E. Tseng, J. Asgari, F. Borrelli, and D. Hrovat, “Integrated Braking and Steering Model Predictive Control Approach in Autonomous Vehicles,” *IFAC Proc. Vol.*, vol. 40, no. 10, pp. 273–278, 2010.

[17] F. Kalim, J. Jeong, and M. U. Ilyas, “CRATER: A Crowd Sensing Application to Estimate Road Conditions,” *IEEE Access*, vol. 4, pp. 8317–8326, 2016.

[18] A. Basavaraju, J. Du, F. Zhou, and J. Ji, “A Machine Learning Approach to Road Surface Anomaly Assessment Using Smartphone Sensors,” *IEEE Sens. J.*, vol. 20, no. 5, pp. 2635–2647, 2020.

[19] Y. Pan, X. Zhang, G. Cervone, and L. Yang, “Detection of Asphalt Pavement Potholes and Cracks Based on the Unmanned Aerial Vehicle Multispectral Imagery,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 11, no. 10, pp. 3701–3712, 2018.

[20] H. Wang, N. Huo, J. Li, K. Wang, and Z. Wang, "A Road Quality Detection Method Based on the Mahalanobis-Taguchi System," *IEEE Access*, vol. 6, pp. 29078–29087, 2018.
[21] J. Dib, K. Sirlantzis, and G. Howells, "A Review on Negative Road Anomaly Detection Methods," *IEEE Access*, vol. 8, pp. 57298–57316, 2020.
[22] J. Cao, C. Song, S. Peng, S. Song, X. Zhang, and F. Xiao, "Trajectory Tracking Control Algorithm for Autonomous Vehicle Considering Cornering Characteristics," *IEEE Access*, vol. 8, pp. 59470–59484, 2020.
[23] L. Tang, F. Yan, B. Zou, K. Wang, and C. Lv, "An improved kinematic model predictive control for high-speed path tracking of autonomous vehicles," *IEEE Access*, vol. 8, pp. 51400–51413, 2020.
[24] G. V. Lakhekar, L. M. Waghmare, P. G. Jadhav, and R. G. Roy, "Robust Diving Motion Control of an Autonomous Underwater Vehicle Using Adaptive Neuro-Fuzzy Sliding Mode Technique," *IEEE Access*, vol. 8, pp. 109891–109904, 2020.
[25] S. An *et al.*, "Control Design for the Autonomous Horizontal Takeoff Phase of the Reusable Launch Vehicles," *IEEE Access*, vol. 8, pp. 109015–109027, 2020.
[26] G. Yadav, S. Maheshwari, and A. Agarwal, "Contrast limited adaptive histogram equalization based enhancement for real time video system," in *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Delhi, India, 2014*, 2014, pp. 2392–2397.
[27] D. Bhattacharyya, J. Dutta, P. Das, R. Bandyopadhyay, S. K. Bandyopadhyay, and T. Kim, "Discrete Fourier Transformation based Image Authentication technique," in *2009 8th IEEE International Conference on Cognitive Informatics, Hong Kong, China, 2009*, 2009, pp. 196–200.
[28] X. Lei, Z. Zhang, and P. Dong, "Dynamic Path Planning of Unknown Environment Based on Deep Reinforcement Learning," *J. Robot.*, vol. 2018, pp. 1–10, 2018.
[29] B. Sri Kaloko, mr. Soebagio, and M. Hery Purnomo, "Design and Development of Small Electric Vehicle using MATLAB/Simulink," *Int. J. Comput. Appl.*, vol. 24, no. 6, pp. 19–23, 2011.
[30] V. D. Thanh and C. T. Minh, "A Universal Dynamic and Kinematic Model of Vehicles," *2015 IEEE Veh. Power Propuls. Conf. VPPC 2015 - Proc.*, pp. 1–6, 2015.
[31] A. Iervolino, R., & Sakhnevych, "Modeling, Simulation and Control of a 4WD Electric Vehicle with In-Wheel Motors.," in *International Conference on Robotics in Alpe-Adria Danube Region. Springer, Cham.*, 2017, pp. 444–455.
[32] E. Kayacan and J. Peschel, "Robust Model Predictive Control of Systems by Modeling Mismatched Uncertainty," *IFAC-PapersOnLine*, vol. 49, no. 18, pp. 265–269, 2016.
[33] Y. Gao, "Model Predictive Control for Autonomous and Semiautonomous Vehicles," 2014.
[34] R. Soloperto, M. A. Müller, S. Trimpe, and F. Allgöwer, "Learning-Based Robust Model Predictive Control with State-Dependent Uncertainty," *IFAC-PapersOnLine*, vol. 51, no. 20, pp. 442–447, 2018.

[1] I. Barabás, A. Todoruţ, N. Cordoş, and A. Molea, "Current challenges in autonomous driving," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 252, no. 2017, pp. 1–6, 2017.
[2] Q. Pham, "Autonomous vehicles and their impact on road transportation," JAMK University of Applied Sciences, 2018.
[3] S. Pendleton *et al.*, "Perception, Planning, Control, and Coordination for Autonomous Vehicles," *Machines*, vol. 5, no. 6, pp. 1–54, 2017.
[4] S. J. Babak, S. A. Hussain, B. Karakas, and S. Cetin, "Control of autonomous ground vehicles: A brief technical review," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 224, no. 2017, pp. 1–6, 2017.
[5] S. A. Bagloee, M. Tavana, M. Asadi, and T. Oliver, "Autonomous vehicles: challenges, opportunities, and future implications for transportation policies," *J. Mod. Transp.*, vol. 24, no. 4, pp. 284–303, 2016.
[6] H. Wazoh, S. Daku, and F. G. Samuel, "Investigative Study Of Possible Causes Of Failure Of A Section Of Road In Jos- Plateau , North - Central Nigeria," *J. Multidiscip. Eng. Sci. Stud.*, vol. 2, no. 11, pp. 1128–1132, 2016.
[7] A. E. Moses and A. A. Fortunatus, "The Use of GIS in the Spatial Distribution of Speed Bumps within Afikpo," *J. Geogr. Environ. Earth Sci.*, vol. 12, no. 1, pp. 1–7, 2017.
[8] J. M. Celaya-padilla *et al.*, "Speed Bump Detection Using Accelerometric," *Sensors*, vol. 18, pp. 1–13, 2018.
[9] G. C. Enwerem and G. A. Ali, "Economic Effects of Bad Roads on Vehicle Maintenance in Nigeria," *Int. J. Sci. Res. Publ.*, vol. 6, no. 6, pp. 761–766, 2016.
[10] S. Rahman, S. Ullah, and S. Ullah, "Obstacle Detection in Indoor Environment for Visually Impaired Using Mobile Camera," *J. Phys. Conf. Ser.*, vol. 960, no. 1, pp. 0–7, 2018.
[11] Y. Zhu, B. Yi, and T. Guo, "A Simple Outdoor Environment Obstacle Detection Method Based on Information Fusion of Depth and Infrared," *J. Robot.*, vol. 2016, pp. 1–10, 2016.
[12] K. Vasavi and M. V. S. Praveen, "Obstacle Detection and Avoidance Autonomous Car," *Int. J. Eng. Trends Technol.*, vol. 9, no. 15, pp. 783–790, 2014.
[13] D. Xie, Y. Xu, and R. Wang, "Obstacle detection and tracking method for autonomous vehicle based on three-dimensional LiDAR," *Int. J. Adv. Robot. Syst.*, vol. 2019, pp. 1–13, 2019.
[14] L. Bascetta, G. Ferretti, M. Matteucci, and M. Bossi, "LFT-based MPC Control of an Autonomous Vehicle," *IFAC-PapersOnLine*, vol. 49, no. 15, pp. 7–12, 2016.
[15] F. Borrelli, P. Falcone, T. Keviczky, J. Asgari, and D. Hrovat, "MPC-based approach to active steering for autonomous vehicle systems," *Int. J. Veh. Auton. Syst.*, vol. 3, no. 2, pp. 265–291, 2005.

[16] P. Falcone, H. E. Tseng, J. Asgari, F. Borrelli, and D. Hrovat, “Integrated Braking and Steering Model Predictive Control Approach in Autonomous Vehicles,” *IFAC Proc. Vol.*, vol. 40, no. 10, pp. 273–278, 2010.

[17] F. Kalim, J. Jeong, and M. U. Ilyas, “CRATER: A Crowd Sensing Application to Estimate Road Conditions,” *IEEE Access*, vol. 4, pp. 8317–8326, 2016.

[18] A. Basavaraju, J. Du, F. Zhou, and J. Ji, “A Machine Learning Approach to Road Surface Anomaly Assessment Using Smartphone Sensors,” *IEEE Sens. J.*, vol. 20, no. 5, pp. 2635–2647, 2020.

[19] Y. Pan, X. Zhang, G. Cervone, and L. Yang, “Detection of Asphalt Pavement Potholes and Cracks Based on the Unmanned Aerial Vehicle Multispectral Imagery,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 11, no. 10, pp. 3701–3712, 2018.

[20] H. Wang, N. Huo, J. Li, K. Wang, and Z. Wang, “A Road Quality Detection Method Based on the Mahalanobis-Taguchi System,” *IEEE Access*, vol. 6, pp. 29078–29087, 2018.

[21] J. Dib, K. Sirlantzis, and G. Howells, “A Review on Negative Road Anomaly Detection Methods,” *IEEE Access*, vol. 8, pp. 57298–57316, 2020.

[22] J. Cao, C. Song, S. Peng, S. Song, X. Zhang, and F. Xiao, “Trajectory Tracking Control Algorithm for Autonomous Vehicle Considering Cornering Characteristics,” *IEEE Access*, vol. 8, pp. 59470–59484, 2020.

[23] L. Tang, F. Yan, B. Zou, K. Wang, and C. Lv, “An improved kinematic model predictive control for high-speed path tracking of autonomous vehicles,” *IEEE Access*, vol. 8, pp. 51400–51413, 2020.

[24] G. V. Lakhekar, L. M. Waghmare, P. G. Jadhav, and R. G. Roy, “Robust Diving Motion Control of an Autonomous Underwater Vehicle Using Adaptive Neuro-Fuzzy Sliding Mode Technique,” *IEEE Access*, vol. 8, pp. 109891–109904, 2020.

[25] S. An *et al.*, “Control Design for the Autonomous Horizontal Takeoff Phase of the Reusable Launch Vehicles,” *IEEE Access*, vol. 8, pp. 109015–109027, 2020.

[26] G. Yadav, S. Maheshwari, and A. Agarwal, “Contrast limited adaptive histogram equalization based enhancement for real time video system,” in *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Delhi, India, 2014*, 2014, pp. 2392–2397.

[27] D. Bhattacharyya, J. Dutta, P. Das, R. Bandyopadhyay, S. K. Bandyopadhyay, and T. Kim, “Discrete Fourier Transformation based Image Authentication technique,” in *2009 8th IEEE International Conference on Cognitive Informatics, Hong Kong, China, 2009*, 2009, pp. 196–200.

[28] X. Lei, Z. Zhang, and P. Dong, “Dynamic Path Planning of Unknown Environment Based on Deep Reinforcement Learning,” *J. Robot.*, vol. 2018, pp. 1–10, 2018.

[29] B. Sri Kaloko, mr. Soebagio, and M. Hery Purnomo, “Design and Development of Small Electric Vehicle using MATLAB/Simulink,” *Int. J. Comput. Appl.*, vol. 24, no. 6, pp. 19–23, 2011.

[30] V. D. Thanh and C. T. Minh, “A Universal Dynamic and Kinematic Model of Vehicles,” *2015 IEEE Veh. Power Propuls. Conf. VPPC 2015 - Proc.*, pp. 1–6, 2015.

[31] A. Iervolino, R., & Sakhnevych, “Modeling, Simulation and Control of a 4WD Electric Vehicle with In-Wheel Motors.,” in *International Conference on Robotics in Alpe-Adria Danube Region. Springer, Cham.*, 2017, pp. 444–455.

[32] E. Kayacan and J. Peschel, “Robust Model Predictive Control of Systems by Modeling Mismatched Uncertainty,” *IFAC-PapersOnLine*, vol. 49, no. 18, pp. 265–269, 2016.

[33] Y. Gao, “Model Predictive Control for Autonomous and Semiautonomous Vehicles,” 2014.

[34] R. Soloperto, M. A. Müller, S. Trimpe, and F. Allgöwer, “Learning-Based Robust Model Predictive Control with State-Dependent Uncertainty,” *IFAC-PapersOnLine*, vol. 51, no. 20, pp. 442–447, 2018.