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Implementation of Birds Detection System using the YOLOv5 Model

Durodola Folasade*, Eludiora Safiriyu, Owoeye Samuel, Makinde Kayode, Folaranmi Olaniyi, Kamil-Bello Furqan, Daodu Sakira

Abstract: This work considers a bird detection system using the YOLOv5 model in handling the challenge of avian-induced crop damages in agriculture. In this study, machine learning and mechatronics will be combined to develop an effective adaptive bird deterrent system. The methodology of the study will comprise data collection from farms and Kaggle, data augmentation techniques, and implementation on Google Colab. The baseline models developed with primary and secondary datasets are compared with a hybrid model and principal model on an augmented dataset containing 14,500 samples. Results show the impact of both dataset size and augmentation techniques is on model performance. The Hybrid Model returned a true positive rate for bird detection as high as 89%, while the principal model had further improvements, returning an accuracy of 85% in bird-type classification. The research proves that augmentation, diversity of datasets, and threshold optimization are three relevant areas related to the robustness of models for bird detection. Future work could be done by increasing dataset size, fine-tuning the model, and fusing multiple modalities to enhance real-world performance.

Keywords: artificial intelligence; bird identification; data augmentation; precision agriculture; YOLOv5

1 INTRODUCTION

For modern agriculture with rapidly changing times, the potential threat from avian species to crop yields has grown, demanding innovative solutions. The task of food security gets incrementally tricky as populations are on the rise worldwide and need scrutiny of threats to crops [1]. Birds, in search of food, often cause substantial damage to crops, and control measures proved to be responsive to date.

The economic burden of bird-related crop damage is substantial, with foraging flocks causing yield reductions and significant losses for farmers worldwide [2]. Beyond immediate yield reductions, this problem contributes to increased pesticide use, additional labour for manual bird control measures, and potential long-term environmental consequences. Traditional methods, like scarecrows and netting, have their inefficiencies in that avian species can get used to stationary deterrents quite fast, and physical barriers may be labour-intensive, not to mention costly [3].

This work is motivated by the need to develop innovative and efficient mechanisms of bird scaring for crop protection. Specifically, it aims to explore the yet unexplored potential of integrating machine learning with mechatronics in such systems, driven by a major concern of alleviating major shortcomings of current agricultural methods [4]. Integrating machine learning with mechatronic systems opens one potentially productive avenue to formulate more effective and adaptive bird-scaring strategies.

The central objective of the present investigation is to tackle the problem of avian-induced agricultural damage through the development and application of an efficient bird deterrent system, augmented by advancements in machine learning and mechatronics [5]. This study aims to gather and evaluate extensive datasets concerning avian behaviour, agricultural varieties, and ecological conditions, which will provide the basis for formulating machine learning algorithms that can forecast and classify pertinent patterns of bird behaviour. Additionally, the research seeks to develop a system characterized by real-time responsiveness, which adjusts to the evolving behaviours of birds and fluctuating environmental conditions via mechatronic elements [6].

This study is important in that it has the potential to revolutionize agricultural methodologies by offering a new approach to solving the ongoing problem of bird loss of crops. This research intends to provide farmers with an informed and responsive resource by integrating machine learning into avian deterrent systems, and it also falls within the framework of sustainable and precision agriculture as described by Singh in 2022 [7]. The results can also mark the beginning of a new era in crop protection, ushering in a more sustainable methodology in agriculture. This approach does not bring benefits economically immediately but also reduces dependence on chemical pesticides.

The present research encompasses a wide range of agricultural contexts along with variable climatic conditions associated with differences in bird species, behaviours, and ecological situations. Various crops are considered to expand the applicability as much as possible, taking into account that each culture has specific problems regarding damage by birds. Relating to machine learning methods, the research is targeted to develop and enhance algorithms focused on predicting and classifying patterns of bird behaviour using several data sets to train the algorithms with relevant and effective validation provided [8].

The potential economic impact, integration of precision agriculture methods, promotion of environmental sustainability, progress of technological development in the agricultural sector, contributing to global food security, and enhancing crop protection with mechatronic applications justify the research in a similar manner [8-11]. Intending to focus on these pivotal elements, the present research intends to contribute substantially towards the themes of agricultural technology and sustainable farming methodologies.

2 LITERATURE REVIEW

Recent research has focused on developing effective and benign methods to deter birds, in attempts to address the growing need for the control of problematic bird populations

within urban and rural environments. Large aggregations of birds pose a serious threat to human health, safety, and economic assets, particularly in the agriculture and aviation industries [12]. The following review synthesizes key research findings on technology-based bird deterrent approaches by analyzing their methods, results, and limitations.

Laser deterrent systems have been very promising in scattering birds. Goswami et al. [13] tested green lasers at 532 nm against double-crested cormorants for deterrence from aquaculture facilities and found that brushing by the beams created effective avoidance behaviours. The study described some problems encountered in the trials, including habituation over time and reduced effectiveness in light conditions.

It involves research into agricultural pest management and bird scaring using such drone-based systems. Raja et al. [14] developed a drone system that integrated computer vision and herbicide delivery for weed management, realizing an accuracy of 95% in classifying weed plants and high accuracy in targeted herbicide delivery. Duttenhefner et al. [15] developed a drone platform for the management of birds at wetlands, combining real-time assessment of flocks with the deployment of deterrents. This reduced bird numbers within trial plots by up to 60%.

Acoustic deterrents have also been investigated. Klug *et al.* [16] tested magnetic fields as an acoustic deterrent on European starlings and found robust magnetic fields significantly reduced starling occupancy of test sites. Micaelo et al. [17] tested ultrasonic acoustic playbacks; an 80% reduction in bird activity was noted within 50 m of speakers during deterrent playback.

Computer vision techniques have been crucial in developing intelligent bird deterrent systems. For instance, Gavali and Banu [18] built a deep neural network for the visual identification of multiple bird species, obtaining accuracy greater than 90% in classifying 20 species and localizing birds by bounding boxes. This exemplifies the possible automation potential for avian detection and recognition within deterrent systems and ecological surveys.

It is suggested that reinforcement learning may improve the activation of deterrents. Yoo et al. [19] proposed using RL-based control strategies for the adaptive adjustment of bird-repellent measures flown by drones, whereby systems could learn, through environmental feedback, to acquire effective policies without needing pre-programmed directives.

While these studies demonstrate that technology-aided avian deterrence is feasible and has some promising leads, there are many limitations. For example, habituation to deterrent measures following persistent exposure, limited effective distances by which repellent stimuli can deter birds, difficulties in observing and classifying highly variable natural behaviours, and challenges in developing context-sensitive activation of deterrents within uncontrolled situations [9].

Increasingly, deep reinforcement learning, computer vision, and robotics afford major opportunities to help with these issues. Future research should focus on increasing deep learning-based detection training datasets, the development of multimodal sensor fusion to offer analytical redundancy, advancement of mobile and swarming drone systems for both adaptive monitoring and deterrence strategies, and integrated platforms linking real-time assessments of flocks with the triggering of smart deterrence measures and adjustments in light of observed outcomes.

In summary, holistic solutions to integrate these functionalities retain great potential for the development of next-generation, competent, automated systems in handling problems associated with populations of birds in the context of human-wildlife conflicts ethically and sustainably. With continued technological improvement, such systems can become a game-changer toward bird deterrence practices across domains such as agriculture, aviation, and urban management.

3 METHODOLOGY

The control of the population of birds within both the agricultural and industrial environments is rather challenging because of its effect on production and yields. Traditional scaring methods through scarecrows, visual-scaring, and noise-producers are always rendered redundant as birds normally get used to such anticipated moves in very short periods [5]. This paper presents a state-of-the-art avian deterrence system using cutting-edge computer vision methodologies, complemented by acoustic strategies for observing, identifying, and repelling birds from pre-defined regions. The main objective of the system is to enhance productivity by reducing agricultural damage and ecological impacts associated with conventional deterrent methods.

The proposed bird-scaring device integrates numerous technological components of the system in a flexible and responsive solution.

A camera will shoot the images of the birds, which will be fed into the YOLOv5 framework for object detection. This model was chosen because it has high performance and ease of computation and integrates well into the overall complete system. This makes the system very versatile for application in either agricultural or industrial settings where proper control over bird populations would be needed. A dataset containing images of birds in a variety of conditions was created to ensure that the task of bird detection and localization succeeds. It contains images of different species of birds taken under a wide range of environmental conditions, such as light, background, and viewpoint. Data augmentation means were implemented by rotation, scaling, colour jittering, and flipping to make the model more efficient. These techniques bring variety to the train data; hence, the YOLOv5 model generalizes better on unseen scenarios [7].

Thus, the architecture of the YOLOv5 model adopted due to its magnificent performance related to both speed and precision has a backbone feature extractor, a region proposal network, and a head for class and regression [14]. Normally, the backbone of feature extraction is a CNN that plays the role of extracting relevant visual features from the input images. The region proposal network component generates

proposals of bounding boxes and their associated objectness scores, thus identifying areas in the image that may contain birds. The head of classification and regression classifies the objects detected as birds and exactly locates them in the image. YOLOv5 was chosen over other object detection architectures since it has high performance and is flexible enough to be implemented on the chosen hardware.

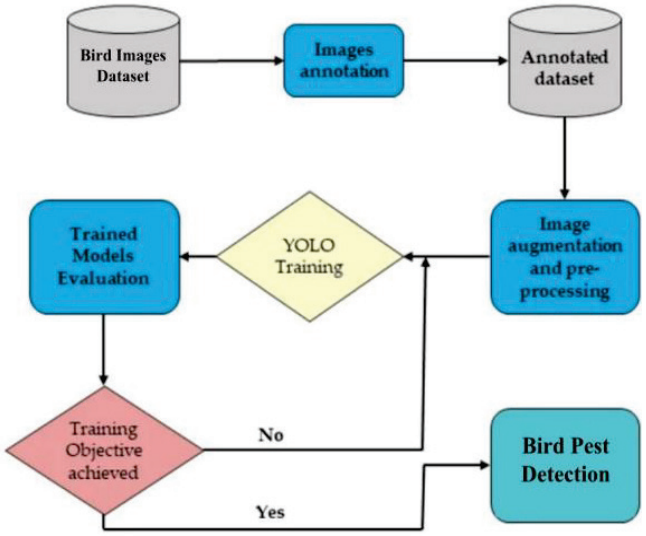


Figure 1 Machine Learning Workflow

The different techniques applied in training the YOLOv5 model included hyperparameter tuning, transfer learning, and data augmentation. It comprises appropriate tuning of parameters like the learning rate, batch size, and regularization factors to ensure a high model efficiency. Transfer learning was used to initialize the model with weights pre-trained on a model by the COCO dataset to enable accelerated convergence and improve the performance outcome. During training, more data augmentation methods were used to strengthen the model's resistance to changes in the input data. A loss function used to train the model was developed deliberately to balance exactly object detection, precise object localization, and accurate object classification. During training, model performance was measured against a validation set with evaluation metrics that included precision, recall, and mean average precision. The overall accuracy and robustness were gradually tuned, based on the evaluation of the model's architecture and training methods.

It was evaluated through a suite of carefully controlled experiments that assessed key metrics for the accuracy of bird detection, operational efficiency, and user satisfaction [4].

Bird detection accuracy was measured in terms of precision, recall, and mAP. Operational efficiency was assessed based on the system's ability to maintain continuous monitoring and deterrence. The satisfaction of the users was assessed through feedback from system operators related to the usability, responsiveness, and overall user experience of the implemented system. Trends and correlations between the detected birds and deterrent effectiveness, together with the environmental situation, were analyzed with data collected during the experimental trials. To identify performance-related issues, a root cause analysis was performed that further aided in improving the YOLOv5 model's performance. That is to say, the detailed methodology adopted in this study provides one with a fresh approach toward avian management within agricultural and industrial disciplines. The bird deterrent system proposed in this particular review shows great promise in productivity improvement, crop loss reduction, and mitigation of the environment. This will give a scalable and integrative approach with sophisticated computer vision and deep learning methodologies that can be tailored to different environments. If refined and improved further, this bird deterrent system can become the key to progress in intelligent and adaptive bird management, hence preserving agricultural production and protecting industrial assets.

4 IMPLEMENTATION AND RESULTS

This is an approach to the full implementation and evaluation of the YOLOv5 framework regarding bird detection, tending to different strategies of augmentation and size changes in datasets. The process began by retrieving the dataset from two major sources: avifauna images in their habitat from farms and the other dataset that was downloaded from Kaggle. These were combined with state-of-the-art augmentation techniques to ensure a reliable and strong dataset for training.

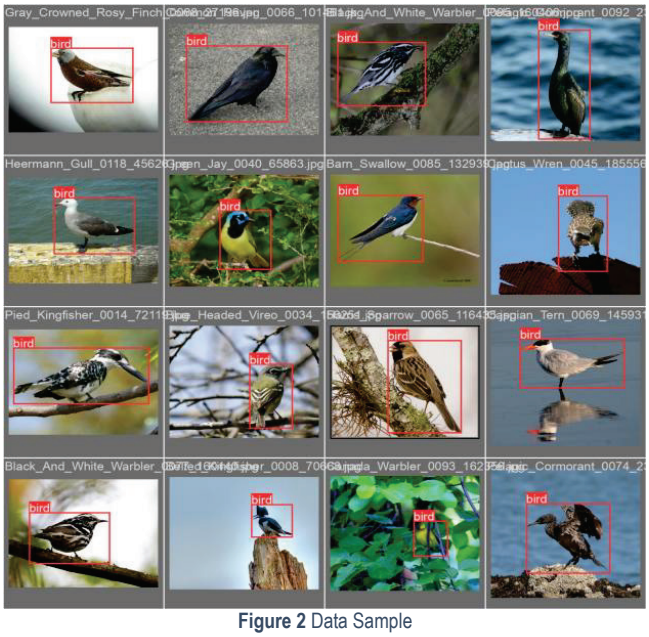


Figure 2 Data Sample

The execution was done within a Google Colab environment, utilizing the cloud-oriented computational resources to scale. This method began with integration in the Google Drive environment within Colab. Hence, making an integral link between Colab's runtime and user storage solutions. Then, clone the YOLOv5 repository from GitHub to ensure that not only could the very latest version be used

but also the entire YOLOv5 ecosystem. Install the necessary dependencies via pip, including the most basic libraries: PyTorch, OpenCV, and Matplotlib.



Figure 3 Environmental Setup

The real crux of the implementation was training the YOLOv5 model. This was called from a command-line interface within the Colab environment, using key parameters that defined the approach to training. An input image size of 640×640 pixels was used to balance accuracy and speed; the batch size was chosen to work in most GPU environments that allow decent training. The number of epochs was chosen to be large enough to pass through the entire training dataset several times. A YAML configuration file was used that defined this model architecture and path of the dataset containing images of birds.

Data augmentation was widely used in this project. The Albumentations library was utilized to create an augmentation pipeline, which included a collection of transformations: rotation, random scaling, flipping, brightness changes, and changes in contrast. All these distortions were constructed with care to simulate different real-life conditions that appear in bird images. This augmentation would be wrapped inside a function, which would loop over all images inside the directory, transforming them and then saving these augmented images with their corresponding labels.

It has gone through various loss functions and performance indicators including box loss, object loss, and classification loss of both the training and validation sets. At the same time, precision, recall, and mean Average Precision (mAP) measured the model's effectiveness in detecting birds.

Results from the implementation gave valuable insights through the various iterations of the model. The baseline model, trained on primary data, showed high precision but recall issues, indicating missed instances of birds. The precision-confidence curve showed a drastic rise to perfect precision at a threshold of 0.632. However, the precision-recall curve showed a dramatic drop in precision for increased recall, which means it is difficult to maintain high precision with increased coverage of a greater proportion of positive bird occurrences.

The secondary data model exhibited outstanding effectiveness, achieving nearly flawless precision and recall across multiple confidence thresholds. The precision-recall curve is closely aligned with the top-right corner of the graph, signifying the model's competence in accurately identifying avian species while successfully detecting nearly all instances within the dataset. Furthermore, the confusion matrix associated with this model revealed impeccable performance in categorizing bird instances and differentiating them from the background.

The hybrid model showed clear improvements by incorporating primary and secondary data. It achieved an 89% true positive rate for bird class detection with perfect specificity. From the F1-confidence curve, one can see that it has a maximum F1 score of 0.89 at the optimum confidence threshold of 0.294 and the relative stability of the F1 score for confidence thresholds between 0.2 and 0.4, which means it maintained an effective balance between precision and recall across different confidence levels.

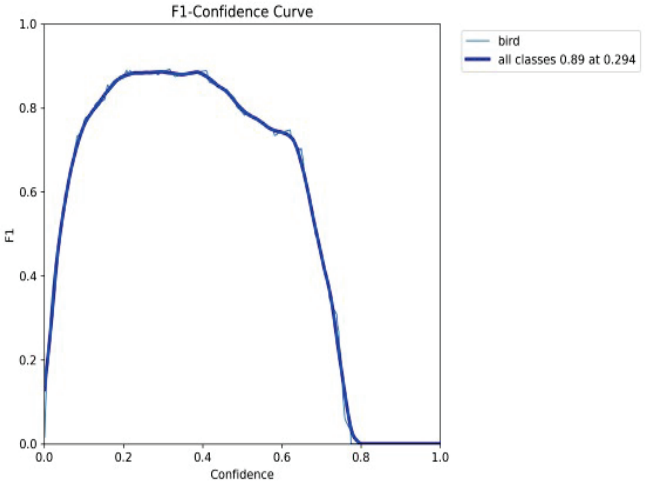


Figure 4 F1 Confidence for Hybrid Model

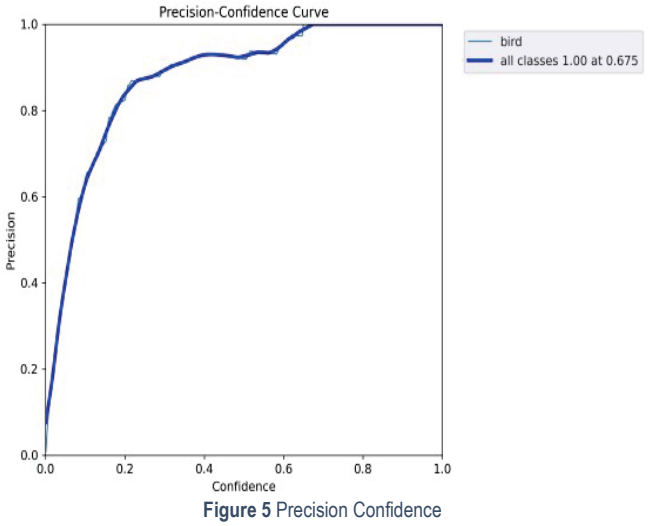


Figure 5 Precision Confidence

The main model trained on the augmented dataset contributed 14,500 samples and showed better performance compared to the previous models. It identified avian species

with an accuracy of 85% and backgrounds with an accuracy of 100%, with a false negative rate for birds of 15%. For the peak F1 score with a confidence threshold of 0.279 and mAP@0.5 of 0.821, the model reached 0.83, indicating its overall effectiveness.

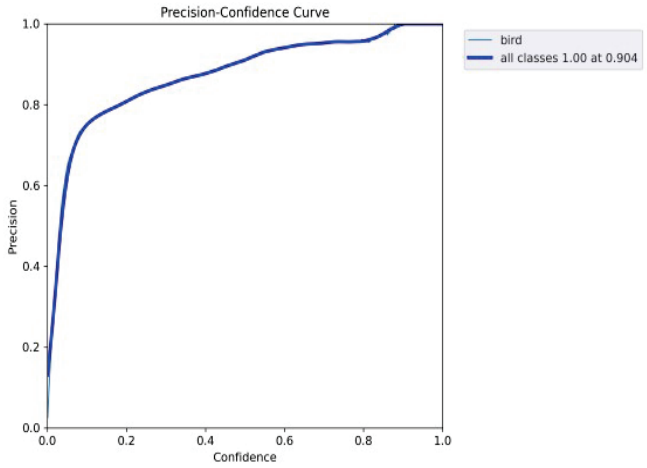


Figure 6 Precision curve

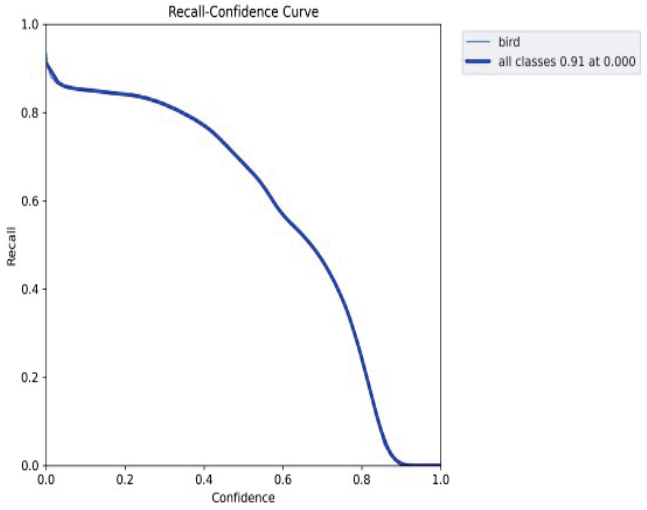


Figure 7 Recall curve

Comparative analysis of these models indicated that dataset size and augmentation strategies are very critical to model performance. Progressive improvement from baseline to hybrid and then to the main model underlined the advantages accruable from increased training data and sophisticated augmentation techniques. It was shown that the main model, having the largest view in the training dataset, performed the best overall, particularly in recognizing the background, with a view of still much room for improvement in reducing false negatives for bird detection.

The paper illustrates the role of data augmentation and dataset size in building robust bird detection models. The methodology of implementation and exhaustive result analysis is provided, offering critical insight into future research in wildlife monitoring applications, especially toward possible future directions of improvement for augmentation methodologies and strategies to reduce false negatives in bird detection.

5 CONCLUSION

The current research demonstrated the strong influence of dataset size, model architecture, and threshold adjustment on the development of effective models for avian detection using the YOLOv5 framework. While the main baseline model achieved high precision, it showed an inability to keep a perfect balance between precision and recall, thus being limited in application in complex scenarios where high recall value is paramount. In contrast, the secondary model trained with another dataset showed almost perfect precision and recall. This indeed shows the importance of dataset quality and relevance for the task at hand.

The hybrid model captured all benefits from the primary and secondary datasets, improving overall detection capabilities while ensuring strong performance in every threshold. This result points to the potential gains to be made from varied datasets for building models. The principal model, trained on the largest dataset, further validated that large training datasets have advantages in model accuracy, particularly in complex scenarios usually encountered in the real world.

These results therefore underscore the need for fine-tuning model training for tasks at hand, dataset composition, and confidence threshold optimization. Improvements seen in both the Hybrid and primary models strongly support the fact that the integration of diverse datasets and the optimization of confidence thresholds can significantly improve detection performance and enable models to adapt to different operational conditions.

Keeping in mind the results from the study, a set of recommendations is given to foster the development of bird detection based on YOLOv5-based models. First, expanding and increasing the diversity of the dataset toward more bird species and environmental scenarios can help the model generalize better and reduce false negatives. Threshold optimization should be application-specific, and each is likely to have some optimum setting; some scenarios may want to keep a low threshold to retain high recall, while others may want a higher threshold for precision-critical applications [8].

Further, there is a need to study fine-tuning the model and methodology for transfer learning with larger or more domain-focused datasets, relating mostly to cases of either rare or hard-to-classify bird species, to improve performance. Besides, the use of additional features and multi-modal data could be able to provide a richer context to make better predictions in more complex environments where visual information alone may not suffice.

Finally, these models should be deployed in live applications and monitored constantly for retraining at frequent intervals. This would help the models get feedback on their performance and adapt to changing conditions continuously, and it would facilitate monitoring and mitigating model degradation over a long time.

These recommendations, when implemented, have the potential to further fine-tune and optimize YOLOv5-based models used in bird detection, making them more effective in real applications. Therefore, not only does this advance the field of computer vision and wildlife monitoring, but it also sets the stage for future research in ecological conservation and biodiversity assessment using state-of-the-art machine learning approaches [10].

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Authors' contacts:

Durodola Folasade
(Corresponding Author)
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria
durodolafo@funaab.edu.ng

Eludiora Safiriyu
Department of Computer Science and Engineering,
Obafemi Awolowo University, Ile Ife, Nigeria

Owoeye Samuel
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria

Makinde Kayode
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria

Folarami Olaniyi
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria

Kamil- Bello Furqan
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria

Daodu Sakira
Department of Mechatronics Engineering,
Federal University of Agriculture, Abeokuta, Nigeria