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A Machine Vision Assisted Automatic Docking System for Power Line Inspection

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Abstract: Power line inspection is a critical task that requires regular monitoring and maintenance to ensure the reliability and safety of electrical distribution infrastructure. With the advancements in robotics, artificial intelligence (AI), and unmanned aerial vehicles (UAVs), integrating robotic manipulators with drones and automating their maneuvers has emerged as a promising solution for power line inspection. This paper proposes a quadcopter design and implementation with a gripper mechanism to dock automatically on a power line using AI-enabled camera feedback. The machine learning model implemented onboard will detect the power line, align the drone to it, and activate the gripper for automated perching. The drone also includes a light weight three degree of freedom (DoF) robotic manipulator with an additional camera incorporated into it for AI-assisted power line inspection. The insulator fault detection can be carried out with a deep learning model. Power line inspection begins with the take-off of the drone from the ground and its perch on the power line. After disarming the drone, the manipulator comes into action. The arm is lifted through a controlled manipulator action to focus the camera on the insulators. The video of the insulators will be shared with a server through wireless means. A custom-trained deep-learning model in the server will identify the faulty insulators.

Keywords: Power line inspection, UAVs, manipulator, degree of freedom, payload capability, deep learning.

I. INTRODUCTION

The structural integrity and robustness of power line components and infrastructure are assessed through a variety of techniques in power line inspection [1], [2]. Visual inspections are direct observations carried out by people at the power lines and related parts for any indications of wear, damage, or potential risks. Aerial inspections make rapid work of covering huge regions by using manned aircraft to conduct visual assessments from an elevated position. The popularity of drone-based inspections has grown because of their affordability and accessibility. Drones can fly near to electrical wires [3] while carrying cameras or sensors to take high-resolution videos and photos. By using laser sensors to create precise 3D models of power line structures, LiDAR technology aids in the detection of spatial correlations and anomalies. Infrared cameras are used in thermal imaging inspections to locate hotspots or improper connections that could be signs of electrical problems. Using specialized equipment [4], [5], ultrasonic testing can find weaknesses or abnormalities in power line conductors. Installing sensors throughout the lines as part of power line monitoring systems allows continuous monitoring of variables like temperature, vibration, and current while also giving real-time data for problem diagnosis and maintenance. A mix of these techniques may be used, depending on the needs to guarantee thorough examination and upkeep of power line infrastructure.

Combining robotic manipulators and drones for power line inspection offers several potential advantages that could greatly improve the process efficiency, safety, and its effectiveness [6], [7]. Drones and robotic manipulators [8] work together to increase safety by minimizing the need for human intervention in dangerous areas. Remote inspections reduce the possibility of falls, electrocution, and other possible hazards brought on by conventional methods. This preserves the safety of the inspection team while gathering precise information. Overall, using robotic manipulators and drones together to examine electricity lines has advantages like better access to difficult-to-reach places, increased safety, increased efficiency, precise manipulation and placement, real-time data collecting, automation, and advanced analytics [9]. These benefits result in better planning for maintenance, earlier problem diagnosis, and increased overall dependability of power line infrastructure.

Related works on drones with manipulators for power line inspection [10], highlight the increasing interest in utilizing aerial robotics and manipulative capabilities to enhance the efficiency and safety of powerline maintenance and inspection operations. Various aspects of this technology have been explored [11], aiming to address the challenges associated with traditional inspection methods and improve overall inspection effectiveness [12]. One area of focus in related works involves the integration of manipulators onto drones [13], [14] enabling them to perform precise tasks such as visual inspection, component maintenance, and repair.

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These manipulators provide the necessary dexterity to access and assess powerline components in detail, facilitating timely interventions and reducing the need for human workers to perform potentially hazardous tasks. Moreover, investigations have been conducted on the use of multirotor drones or micro-UAVs for power line inspection [15]. These platforms offer increased agility and maneuverability, allowing them to navigate complex powerline structures, such as transmission towers and overhead lines. This capability enables comprehensive visual coverage and facilitates detailed inspections of powerline infrastructure.

Autonomous powerline inspection systems have also garnered attention in related works. The development of intelligent algorithms and sensing technologies to enable drones with manipulators to autonomously perform inspection tasks has been explored in [16], [17]. By reducing the reliance on human operators, these systems enhance operational efficiency, minimize human error, and improve overall inspection accuracy. Sensors play a vital role in powerline inspection, and related works have focused on integrating advanced sensor technologies. High-resolution cameras, LiDAR, thermal imaging devices, and other sensors have been employed to capture precise measurements, detect defects or anomalies, and enable real-time monitoring of powerline conditions. The incorporation of these sensors enhances the quality of data collected during inspections and contributes to more informed decision making. Control strategies and algorithms are another critical aspect addressed in related works. Control systems to ensure stable flight [18], accurate manipulation, and obstacle avoidance capabilities during power line inspection missions [19], has been proposed. These control systems play a crucial role in maintaining the safety and reliability of drone-manipulator systems, enabling them to operate effectively in challenging environments. Furthermore, research efforts have been directed towards optimizing the overall system design of drones with manipulators, for powerline inspection. This includes considerations such as payload capacity, power supply, endurance, and robustness, aiming to develop reliable and efficient platforms specifically tailored for power line inspection applications. Collaborative efforts and interdisciplinary approaches have also emerged in related works [20], with researchers integrating expertise from various fields such as robotics, power engineering, and computer vision. This collaborative approach [21] ensures a comprehensive understanding of the challenges and requirements of powerline inspection, leading to more effective solutions.

Here, we propose a power line inspection drone that is capable of perching automatically onto the high-tension line using its onboard machine learning model. It can inspect the line using a 3 DoF arm with a camera as its end-effector and feed this video to a server in real time. The server has a custom trained deep learning model, which can automatically identify faults in the electrical components such as insulators.

II. METHODOLOGY

The main objectives of this work are to (A) develop an aerial robot equipped with a gripper module and (B) a 3 DoF arm to do a vision-based automated perching and inspection of power line components. This gripper is mounted on top of the airframe and is designed to secure the robot in a stable position at high altitudes. Our proposed system enables the robot to attach its frame to a power line located above it. This setup allows for aerial manipulation operations when the gripper successfully captures and connects to an object. While the UAV itself is manually controlled via remote controls, precise positioning and management of the robotic gripper require autonomous, vision-based control. Once the perching is successful, the robotic arm should be expanded to do a visual inspection of the power-line components like the insulators by sending a live video to a server. On the server a YOLO-based machine learning model is implemented that can detect the faulty insulators.

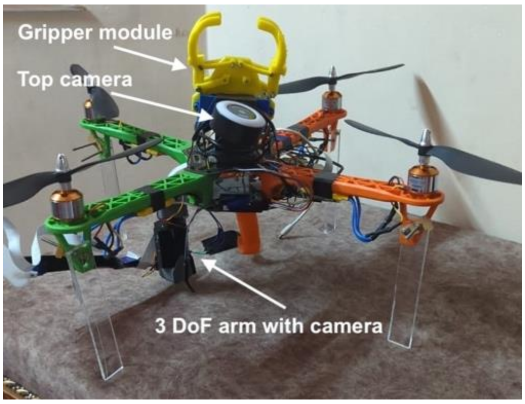

Fig. 1. The drone with gripper module, top-camera, 3 DoF arm and an arm camera.

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2.1 The AI Enabled Gripper Module

A webcam mounted on top of the drone captures a real-time video feed of its surroundings as in Fig. 1. This feed is processed using image processing and machine learning techniques to analyze and extract relevant information. The processed image is used to identify and track nearby power lines. Based on the detected power lines, control commands can be sent to the drone's flight controller system to navigate it towards the power line, and align itself along the power line. Then the gripper on the drone operates automatically, closing in response to received control commands, perching onto the power line.

2.2 The Vision Assisted 3 DoF Arm

The proposed methodology for insulator fault detection using a 3DOF drone equipped with a manipulator as in Fig. 1and an integrated YOLO algorithm, with a camera mounted at the end effector, is a comprehensive and innovative approach. The first step involves designing and building of the drone with the manipulator capable of carrying the camera and performing manipulative tasks. The camera is strategically placed at the end effector to capture high-resolution images or videos of powerline insulators during the inspection process. A dataset of labeled images is collected, containing both faulty and non-faulty insulators, which is then used to train the YOLO algorithm for object detection and classification.

After preprocessing and splitting the dataset into training and testing sets, the YOLO algorithm is fine-tuned specifically for insulator fault detection, ensuring optimized performance. Once the YOLO model is trained, it is implemented on the drone's onboard computer for real-time object detection. The drone is programmed with navigation and path planning algorithms to ensure it hovers close to powerline insulators, and the manipulator is controlled to position the camera for detailed inspection.

During the inspection process, the camera captures images, and the YOLO algorithm analyzes them in real-time to detect faulty insulators. The algorithm's outputs are then processed to assess the severity of the faults and their potential impact on the powerline integrity. The drone's decision-making algorithms prioritize, and report detected faults based on their severity. Real-time data and inspection reports are transmitted to operators or a centralized control system for further action.

Using the proposed UAV, our procedure for performing aerial manipulation at high altitudes includes the following steps.

- Flying to the designated work area.
- Grasping the desired power line to stabilize and secure the robot frame.
- Conducting the manipulation task, which, in this case, involves inspecting the insulator for faults.
- Disengaging and landing.

2.3 Design

The design of the drone includes the following major subsections.

A. **Drone Frame Design**

Fig. 2. The frame of the quadcopter's skeleton, where various components are mounted.

To build the quadcopter, one must start by selecting a suitable frame and affixing four brushless motors that provide the necessary thrust for flight as shown in Fig. 2 Matching propellers are then chosen to ensure optimal lift and stability. Fig.3 shows the quad copter manipulator design in Fusion360®.

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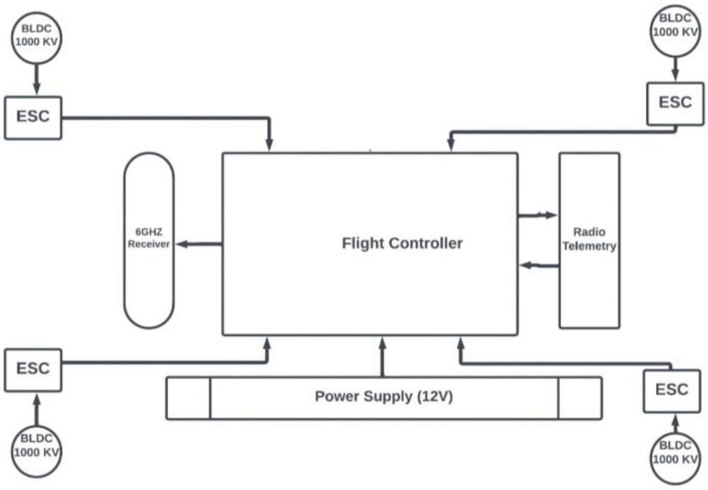

Fig. 3. Block diagram of drone. The flight controller, ESC, and BLDC motor, while the radio telemetry and receiver enable communication between the drone and the ground.

Electronic speed controllers (ESCs) and necessary peripherals as shown in Fig. 3 are connected to the motors and flight controller, regulating motor speed based on inputs received from the KK2.1.5. Pairing the flight controller with a compatible radio transmitter and receiver allows for seamless remote control. A power distribution board is implemented to efficiently channel power from the battery to the flight controller and ESCs. Following the assembly of all components onto the frame and proper wiring, the flight controller is calibrated using the built-in menu system. This crucial step ensures accurate orientation and enables fine-tuning of control settings for stable flight.

B. **Gripper Module Design**

(a) Gripper design– side view. (b) Gripper design – isometric view

Fig. 4. 3D model of the gripper design in Fusion360® attached to the upper body of the drone.

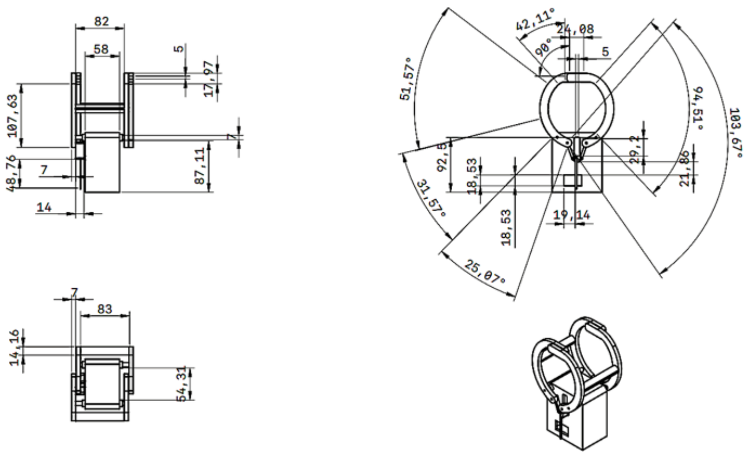

Fig. 5. Dimensions of gripper module.

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The gripper module consists of several components, including gripper jaws, an electric actuator, a transmission element, a base, and linkages as in Fig. 4. This module features a twin-finger arrangement, with its motion controlled by spur gears. The motor is coupled with the spur gear; as the motor rotates, the spur gear engages, enabling the gripper's movement. The fingers of the gripper move to grasp objects, providing a simple yet effective design. At the point of contact, the gripping force is always perpendicular to the surface, ensuring maximum grip strength on the object.

Fig. 6. Arm design in Fusion360® attached to the lower body of the drone.

Additionally, the location of the contact points does not affect the gripping force. The jaws use frictional force to secure the item, and an electric actuator drives the spur gears to open the jaws. The connecting link rotates using these gears, facilitating the gripping action. The design dimensions of the gripper are detailed in Fig. 5.

C. **Manipulator System Design**

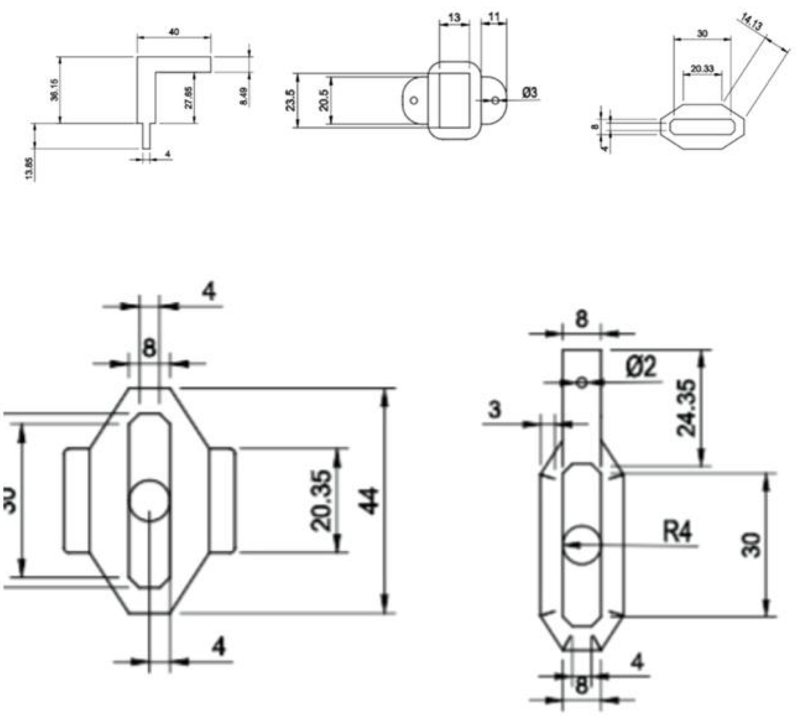

Fig. 7. Dimensions of arm module.

With the help of a battery as a counter balance, the manipulator is fixed to the base side of the aerial vehicle. Four motors are placed on the tip of the quadcopter's X-shaped frame construction as shown in Fig. 6.

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Each motor's propeller, which produces downward thrust as it turns, is fixed to the top of the motor. To regulate the thrust, the motor's rotations per minute (RPM) are altered.
The first motor of the manipulator is mounted on a holder that is bolted to the drone. OneDoF revolute joints are used to serially connect three links. As a result, the manipulator has three degrees of freedom (DoF) and is an RRR arm. Mechanical servo motors with rotational axes of 180° or 360°power the joints.A servo motor is a kind of actuator that offers rotary or linear motion as well as feedback on the present location. The links are connected to the servo motor's shaft, which rotates to position the links at the proper rotatory angle. The end of the third link has an end-effector attached to it. Depending on the task, the end-effector could be a camera, a gripper, or any other device. Here, we use a camera for the inspection work.The manipulator was designed in Fusion 360®, and the dimension sketches are shown in Fig. 7. The final model of the drone attached to the gripper module and the arm, is shown in Fig. 8.

2.4 3D printing

The arm in this design was 3D printed to ensure strength and reduce weight. Poly Lactic Acid (PLA) material was used to 3D print the gripper module and the manipulator pieces.All the connections were tightened as well to increase their durability.The total weight of the manipulator with motors is 93 grams. Since two motors were being used as servos, each link's motor connection point had a unique design. Depending on the task, the lower portion of the last link was kept as flattened to accommodate any needed end-effector. To ensure strength with little weight was a top priority when printing the arm.

2.5 Controlling manipulator

Tkinter, a Python library for creating graphical user interfaces (GUIs), can be used effectively to control motor rotation. First, the necessary hardware interface is established to connect the GUI with the motor. Using Tkinter, GUI elements such as buttons or sliders are created to represent motor control parameters. Event-driven programming in Tkinter enables the definition of functions to handle user interactions with these GUI elements.

Fig. 8. Final design of the drone in Fusion360® where both the gripper and the arm are attached.

III. MATHEMATICAL MODELING

Mathematical modeling of the drone primarily includes the calculation of empty weight fraction and Denavit-Hartenberg (D-H) parameters for the 3 DoF arm, as discussed in the following subsections.

3.1 Weight

The weight of each component should be taken into consideration for calculating the empty weight and total carrying weight. The calculations of weight estimation are as follows.

$$W_T = W_F + W_M + W_{ES} + W_{Batt} + W_{Pay}$$

Where W_T, W_F, W_M, W_{ES}, W_{Batt}, and W_{Pay} represent the takeoff gross weight, frame weight, motor weight, ESC's weight, battery weight, and payload weight, respectively.
The empty weight can be calculated as

$$W_e = W_F + W_M + W_{ES}$$

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If the quadcopter is electrically equipped, the takeoff gross weight will remain constant. Thus, the total gross weight is given by

$$W_T = W_e + W_{Batt} + W_{Pay}$$

The empty weight fraction is then computed as

$$Empty\ Weight\ Fraction = \frac{W_e}{W_T}$$

3.2 Denavit-Hartenberg Parameters

The Denavit-Hartenberg Convention is used to determine the forward and inverse Kinematics Solution. The manipulator's mobility will be controlled using these solutions. The Kinematics and Inverse Kinematics solution for each leg are calculated using four D-H parameters as shown in Fig. 9.

1) Twist angle $\propto_{i-1}$: The angle between the lines along joints$i-1$and i measured about $\hat{X}_{i-1}$which is the common perpendicular.
2) Link length a_{i-1}: The distance between the lines $i-1$ and i.
3) Link offset d_i: The distance along $\hat{Z}_i$ from the line parallel to $\hat{X}_{i-1}$ to the line parallel to $\hat{X}_i$.
4) Rotation angle θ_i: The angle between $\hat{X}_{i-1}$ and $\hat{X}_i$ measured about $\hat{Z}_i$.

This method for calculating D-H parameters only takes into account rotary or prismatic joints with a single degree of freedom. Any joint with more than one degree of freedom is regarded as having several 1DoF joints. For a prismatic joint, the parameter d_i will have a variable value whereas the parameter θ_i will be constant. In contrast, for a rotary joint, the parameter θ_i will be changeable and the parameter d_i will always have the same value. Other parameters may have negative values even though the value of a_{i-1} is always positive.

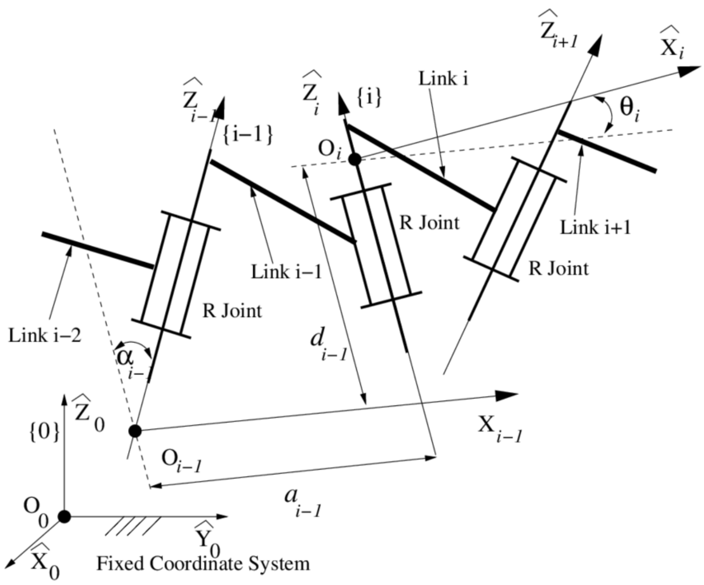

Fig. 9. Intermediate links and D-H parameters.

3.3 Jacobian Matrix

To determine the subsystem linear and angular velocities, the Jacobian matrix (J) is used. The Jacobian matrix can be obtained by formulating the linear and angular velocity vectors as a matrix equation. The coefficient matrix is what relates to the derivative of the state. The components of J are nonlinear functions of states, and for a non-autonomous system, J will be a function of time. The matrix's linear and angular velocity components are typically expressed as two halves and $J \in R^{m*n}$, where m is the number of coordinates required to represent the motion in Cartesian space and n is the dimension of the state vector. By obtaining the inverse of the J matrix, we can calculate the necessary joint variable velocities for the supplied linear and angular velocities. For this function to occur, the J matrix's determinant must not be zero. Robotics singularity analysis primarily depends on the Jacobian matrix.

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3.4 System Modeling

Kinematics equations and dynamics equations are the two types of calculations used in robotics to explain each individual robot. The kinematics equations describe the system's kinematics, or the way the end-effector motion differs once the joint variables change. It does not take into account the cause of the change.

The dynamics of a system, on the other hand, consider the cause of motion. The dynamics of a model is expressed by its equations of motion. This unique collection of equations of a particular plant, which involve macroscopic characteristics like weight, moment of inertia, and so on, are characterized by joint variables or systemic states. The final design of the arm is as shown in Fig. 10, when attached to the drone frame along with the end effector camera. Fig. 1 shows the complete implementation of the drone system with the gripper module and the arm with the end effector camera.

Fig. 10. The manipulator system integration onto the base of a drone. The drone platform's size and modifications accommodate the manipulator, ensuring balance and stability during maneuvers.

IV. DETECTION OF POWER LINES AND ITS ALIGNMENT USING DEEP LEARNING

This approach is also used for detecting objects, specifically power lines. However, it is not integrated with the hardware. Instead, the feed from the webcam is used for analysis. This method provides more accurate results compared to traditional image processing. For power line detection using YOLO, a dataset of 100 custom images was utilized, with 80% of the images allocated for training and 20% for testing. Initially, the training was conducted for 3000 iterations, but the model showed low accuracy and overfitting. Training was then extended to 10,000 iterations, achieving an accuracy of around 80% and significantly reducing the loss function. The model was subsequently employed for detection. The code was executed on Jupyter® Notebook® within a virtual environment, enabling real-time predictions to determine if an object in the video is a power line.

YOLO is a real-time object detection algorithm that operates differently from traditional methods by performing detection in a single pass. The key steps in its operation are as follows.

- Input: The YOLO architecture receives a full image as its input.
- Convolutional Layers: A series of convolutional layers are applied to this input to extract features from the image. The original YOLO model includes 24 convolutional layers followed by 2 fully connected layers. Some versions of YOLO also incorporate max pooling layers.
- Split into Grid: The output from the convolutional layers is divided into an S x S grid. For YOLOv1, S is typically set to 7, creating a 7x7 grid.
- Predictions: Each grid cell generates predictions, specifically B bounding boxes and their associated confidence scores. Additionally, each cell predicts C class probabilities. For YOLO v1, B is usually set to 2.
- Output: The model's output is a tensor with a shape of S x S x (B5 + C). For each bounding box, the model predicts the x and y coordinates of the center, the width, the height, and a confidence score, accounting for B5 parameters. The class predictions add another C parameters.
- Post Processing: The final step involves post-processing the output tensor. Techniques like thresholding on confidence scores and non-maximum suppression are applied to produce the final bounding box predictions.

V. INSULATOR FAULT DETECTION USING DEEP LEARNING

A variety of deep learning methods are available for insulator fault recognition. These deep learning algorithms include YOLO, R-CNN, Fast CNN, and many more.

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The YOLO algorithm is utilized in this work for insulator fault detection,as done for power line alignment detection. YOLO improved prediction accuracy and bounding box intersection over union. The main benefit of YOLO is its quickness. Compared to its competitors, YOLO is a much faster algorithm.

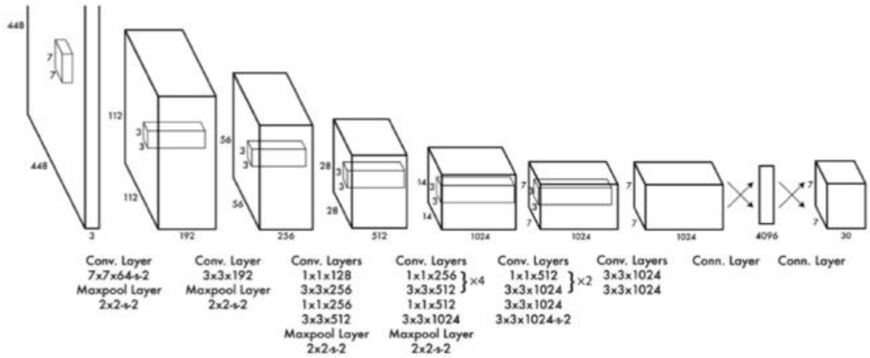

Fig. 11. The deep neural network architecture of YOLO. The detection network has 24 convolutional layers followed by 2 fully connected layers.

YOLO determines the attributes of these bounding boxes using a single regression module in the following format, where Y is the final vector representation for each bounding box.

$$Y = [pc, bx, by, bh, bw, c1, c2]$$

This is important during the training phase of the model. The architecture shown in Fig.11 works as follows. Preprocessing by resizing the input image into 448 x 448 before giving it to the convolutional network. First, to generate a cuboidal output, a 1x1 convolution is applied to reduce the number of channels, followed by a 3x3 convolution. ReLU is the activation function, except for the final layer, which uses a linear activation function. Batch normalization and dropout are then used to regularize the model and prevent it from overfitting.
Collecting the collection of images with and without fault insulators is the first stage in implementation. By creating boundary boxes labeling the fault and no-fault classes, this dataset is used to train the machine. The datasets used for insulator fault detection are from the IEEE data port dataset. For insulator fault detection using YOLO, a dataset consisting of 914 images was used, from which 80% of the images were used for training and 20% for testing. The training was done for 10000 iteration steps, and the training accuracy obtained was around 89% and the loss function was reduced to a small value. The model was then used for detection. The code is executed on Jupyter® Notebook® running in a virtual environment. Using this model, real-time predictions can be made to determine if the insulator is faulty or not. The precision of the model that we trained is 91%.The mathematical equation for calculating the precision is TP/(TP+FP) where TP is the true positive and FP is the false positive.
The focal loss function will address the imbalance between positive and negative samples in target detection. It is possible to add weight to the loss corresponding to the sample according to the difficulty of sample discrimination, that is, add less weight to the easily distinguishable sample and add greater importance to the complex distinguishable sample. The formula used for the classification loss function is as follows.

$$L_{cls} = -\zeta t(1 - pt)\delta \log(pt)$$

where $L_{cls}$is the classification loss value.p is the probability that the sample predicted by the model belongs to the foreground. To solve the imbalance of sample categories, the weight parameter δ is introduced.

VI. EXPERIMENTAL RESULTS

The experimental results of this work can be discussed in two following subsections, first about the automatic docking system on power lines, and then the power line inspection and fault detection using machine learning techniques.

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6.1 Automatic Docking to Powerline

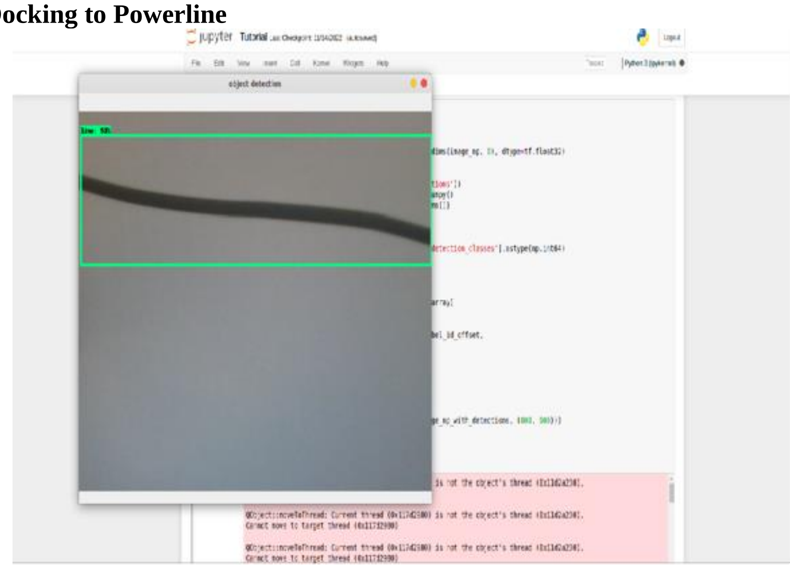

Fig. 12. Power line detection by on-board ML model.

Result-1: The drone was able to carry a payload with stability, containing the gripper, achieving a stable flight to a certain height, and successfully perching onto the identified object. The drone was controlled manually, meaning it was operated using direct control inputs from a human operator. This involves using an RF remote controller to send control signals to the drone, allowing real-time navigation by the pilot. The manual control process involves the pilot using a handheld remote controller with joysticks, buttons, and switches that correspond to different flight controls such as throttle, pitch, roll, and yaw. These controls enable the pilot to adjust the drone's speed, direction, and altitude. During manual control, the pilot relies on visual observation and hand-eye coordination to maneuver the drone. Inputs from the controller are translated into commands that determine the drone's behavior, including changes in speed, rotation, and flight path.
Result-2: The drone is equipped with a gripper mechanism that allows it to interact with objects in its environment, specifically power lines. This gripper enables the drone to securely perch onto power lines. Utilizing image processing techniques powered by YOLO, particularly color code detection, the drone can accurately identify and target power lines. The gripper successfully identified the object of interest and automatically perched onto it. A test maneuver of successful power line detection is shown in Fig. 12 as a screen shot.
This system was tested in a controlled environment, aiming to perch on a line at an altitude of 5 meters above the ground. Out of 25 trials, the system successfully perched on the target 14 times on the first attempt and 11 times on the second attempt. Here, one attempt refers to a direct flight towards the target for perching.

6.2 Power Line Inspection and Insulator Fault Detection

Fig. 13. Insulator fault detection by the ML model running in a remote server. The same results are shared with a mobile phone that has a VNC client running.

Result 1: At the first result, a lightweight manipulator with 3DoF was designed in Fusion360® and implemented in drone.The end effector of the link is also attached with a camera for fault insulator inspection.

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Result 2: Next using deep learning techniques the real time video feed was taken and processed by identifying the insulators as fault or with no fault. Some screenshots are shown in Fig. 13.
Result 3: The drone could lift the manipulator system by considering its payload capacity for the powerline inspection. To achieve a successful lift of the manipulator system, the drone's payload capacity was carefully assessed to ensure that it can handle the additional weight. The structural integrity of the drone was also tested, and necessary reinforcements were made to support the manipulator's weight without compromising stability.

VII. CONCLUSION

The primary goal of the project was to develop and deploy a drone capable of aerial manipulation for executing power line inspections.The integration of machine learning and vision-based gripper technology for drone docking on power lines, represents a transformative advancement in inspection practices. The 3DoF drone equipped with a manipulator system and a camera, integrated with deep learning for insulator fault detection, presents a promising solution for efficient and accurate powerline inspections.The combination of the drone's mobility, the manipulator's dexterity, and the deep learning capabilities of the camera's AI-powered detection system allows for close-up and real-time assessments of powerline insulators. By leveraging and integrating deep learning algorithms, such as YOLO, the drone can rapidly detect and classify faulty insulators with high precision, minimizing the risk of potential power failures and human hazards.
This work proposes the design and implementation of a drone that can automatically perch on electricity wires, effectively inspecting insulators without human intervention. Additionally, the drone's aerial perspective offers a comprehensive view of the power lines, facilitating better detection of defects, malfunctions, and potential hazards. This enhanced monitoring capability ensures the reliability and integrity of the power distribution network, leading to improved overall performance of the grid, and reduced downtime.The drone implemented as a part of this work,performed exceptionally well during the testing phase, demonstrating its ability to navigate challenging situations, and successfully execute inspection tasks. With its safety, efficiency, and cost-effectiveness, it offers a promising and tangible solution to the power line inspection menace

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