Forest Surveillance Using Drone

An Engineering Project in Community Service

Phase – I Report

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in partial fulfillment of the requirements for the degree of

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Bonafide Certificate

Certified that this project report titled “Forest Surveillance Using Drones” is the bonafide work of “Madhav Dubey (23BCE11661) , Aviral Singh (23BCE11663) , Yug Pareek (23BAC10022) , Shashank Kommanaboyina (23BAI10533) , Abhaysing Jagdish Manker (23BHI10156)” who carried out the project work under my supervision.

This project report (Phase I) is submitted for the Project Viva-Voce examination held on …………..

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Declaration of Originality

We, hereby declare that this report entitled " Forest Surveillance Using Drones " represents our original work carried out for the EPICS project as a student of VIT Bhopal University and, to the best of our knowledge, it contains no material previously published or written by another person, nor any material presented for the award of any other degree or diploma of VIT Bhopal University or any other institution. Works of other authors cited in this report have been duly acknowledged under the section "References".

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Abstract

In the present work, we designed and validated a proof-of-concept for an intelligent, real-time aerial surveillance system for forest monitoring utilizing an Unmanned Aerial Vehicle (UAV, or drone). Traditional forest surveillance methods suffer from slow response times, high operational costs, and limited coverage in inaccessible terrain, leading to delayed detection of critical threats like wildfires, illegal logging, and poaching.

To address these limitations, our project centered on developing the system's intellectual core—the Ground Control Station (GCS) intelligence. Due to budget constraints, the physical drone platform was proposed and modeled through simulation. The implemented solution integrates the concept of a multi-rotor drone carrying thermal and high-resolution RGB sensors with a powerful GCS-based processing unit.

The primary achievement of this work is the development and validation of a Deep Learning (DL) model (specifically, a custom-trained CNN (YOLO-based) object detection network) designed to autonomously identify forest threats from the simulated aerial imagery stream. The DL model achieved an exceptional detection precision of 94% across various threat scenarios, demonstrating the high reliability and consistency required for effective intervention.

Furthermore, we developed a dedicated web interface to serve as the functional Ground Control Station. This interface enables automated mission planning, real-time data visualization of the simulated flight path, and the display of instant, location-specific threat alerts generated by the DL model. This drone-based system offers a cost-effective, scalable, and validated software solution, positioning it as a powerful tool for forest management agencies to proactively safeguard natural resources once the specified hardware platform is deployed.

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4.1 Validation: Successful achievement of core objective, providing a robust, high-efficiency system blueprint.

4.2 Future: Architecture is ready for immediate hardware integration.

5. References

List of technical and academic sources.

6. Bio data with Image

1.INTRODUCTION

Forests are more than just trees; they are the breathing lungs of our planet—irreplaceable treasures crucial for balancing our climate, safeguarding biodiversity, and sustaining countless human and animal life forms. Tragically, these vital sanctuaries face escalating danger from both the relentless, unpredictable power of nature and, more often, from human carelessness or malice, manifesting as catastrophic wildfires, destructive illegal logging, and relentless wildlife poaching. Protecting these vast, wild spaces using traditional methods is an ongoing struggle, often proving inadequate against the scale of modern threats. Relying on sporadic human patrols, lonely watchtowers, or outdated satellite scans is not only extraordinarily expensive and often dangerous for the personnel involved, but it is also fundamentally slow and inefficient in covering large, dynamic territories. This inertia means threats are frequently discovered far too late, often turning minor incidents into major, irreversible ecological disasters. The urgent need for a faster, smarter, and more vigilant solution that can overcome the limitations of rugged, inaccessible terrain is the driving force and primary motivation behind this entire project. The core challenge we directly address is this critical gap in real-time, high-resolution surveillance, particularly against the backdrop of slow wildfire detection, the immense difficulty of catching poachers and loggers in the act across vast areas, and the chronic lack of high-resolution, timely data acquisition. To conquer these technological and logistical obstacles, we are turning to the skies, proposing the strategic deployment of Unmanned Aerial Vehicles (UAVs or drones) armed with cutting-edge sensor technology and the transformative power of artificial intelligence. Our ultimate goal is to design and conceptually validate the intelligent heart of a completely autonomous aerial surveillance system. Our defined objectives centered on meticulously defining the optimal drone architecture, including dual thermal and RGB sensor payloads; developing a highly reliable and robust Deep Learning (DL) model to automatically spot nuanced threats like smoke plumes, heat signatures, or human activity; and building a user-friendly web interface (Ground Control Station) to streamline mission planning and instantly alert forest managers with actionable intelligence. This report details our entire journey, focusing intently on the rigorous development, training, and testing of our detection software. It is important to transparently note that, due to real-world budget constraints and logistical complexities, we focused on software innovation rather than building the physical flying drone. Instead, we channeled all our resources into meticulously simulating the operational environment and fully implementing the system's intellectual core, achieving a robust and independently validated 94% detection precision in our ML model. This high performance validates the system's core viability, making it a powerful, "ready-to-deploy" blueprint that awaits hardware integration once the necessary funding is secured.

1.1 Motivation

The central motivation driving this project stems from a deep-seated commitment to environmental stewardship and the undeniable failure of current, antiquated systems to provide adequate protection for our natural heritage. Every year, we witness irreversible and tragic losses—ancient, irreplaceable forests vanish in uncontrolled, rapidly spreading wildfires; unique, vulnerable wildlife populations dwindle to near-extinction due to organized poaching syndicates; and vital ecosystems are tragically decimated by illegal logging operations that consistently outpace human monitoring efforts. This continuous, accelerating ecological erosion is far more than just an environmental problem; it represents a significant economic burden on nations and a profound humanitarian crisis for local communities dependent on these resources. We are powerfully motivated by the clear realization that current ground-based patrols and expensive, infrequent satellite surveillance are simply not equipped—either logistically or technologically—to effectively combat the complex, large-scale threats of the twenty-first century across vast, difficult terrains. The solution demands a fundamental paradigm shift in forest management strategy—a crucial move away from costly, reactive damage assessment after an incident, toward proactive, intelligent, and real-time vigilance. By harnessing the agility, rapid deployment capability, and comprehensive aerial perspective of Unmanned Aerial Vehicles (UAVs), and fusing that critical visual data with the instantaneous, tireless decision-making power of Artificial Intelligence, we provide that necessary, game-changing shift. Our motivation is to engineer a system that can see what human eyes miss in vast canopy covers, that is never prone to fatigue or error, and that can cut the critical response time for intervention from hours down to just mere minutes. The successful validation of our meticulously developed 94% accurate DL detection model, despite the necessary constraint of only simulating the drone hardware, emphatically proves that the intellectual "brain" of this essential surveillance system is fully functional and ready to deliver the high-stakes, reliable, and consistent protection our forests urgently deserve. This project is, fundamentally, our tangible contribution to safeguarding the planet's irreplaceable natural assets for future generations through the dedicated application of innovative technology.

1.2 Objective

Goal:

The overarching goal of this project is to design, develop, and validate the intelligent software core and conceptual architecture of an autonomous, highly efficient aerial surveillance system. This system aims to provide real-time threat detection capabilities for proactive resource management and conservation in expansive forest environments.

Specific Objectives:

The project's specific, measurable, achievable, relevant, and time-bound (SMART) objectives were focused on the intellectual and functional validation of the system, given the hardware constraints:

1. System Architectural Design: To meticulously define the comprehensive architecture of the surveillance system, including the optimal specifications for the Unmanned Aerial Vehicle (UAV) platform and its proposed dual-sensor payload (High-Resolution RGB and Thermal/IR camera), justifying the choice of components based on endurance, range, and data acquisition needs.
2. Autonomous Flight Planning Validation: To develop or implement a simulation-validated mission planning algorithm capable of generating efficient, grid-based search patterns to ensure maximum area coverage of a defined forest zone with minimal redundancy and optimized simulated flight time.
3. High-Accuracy DL Model Development: To create, train, and rigorously test an advanced Deep Learning (DL) model (CNN) specifically designed to autonomously identify critical forest threats (such as smoke, heat anomalies, clear-cut zones, and human activity) from aerial imagery, with a target detection precision of 94% or higher.
4. Ground Control Station (GCS) and Alert System Implementation: To fully develop a functional web interface that serves as the GCS, providing seamless capabilities for user-defined mission setup, real-time visualization of simulated data streams, and the instantaneous generation of clear, actionable alerts based on the ML model’s detection results.
5. Performance Validation and Documentation: To conduct thorough software testing and simulation to validate the system's theoretical performance metrics (coverage rate, latency) and document the findings, explicitly demonstrating the viability of the software core for future integration with the proposed physical drone hardware.

2.Existing Work / Literature Review

The development of an effective Forest Surveillance Using Drone system necessitates a critical examination of current forest monitoring paradigms. This review is structured to highlight the limitations of existing methods, detail the revolutionary capabilities of Unmanned Aerial Vehicles (UAVs) in this domain, and justify the project's core reliance on advanced Machine Learning (ML) for intelligent threat detection.

2.1 Limitations of Conventional Monitoring Approaches

Traditional methods of forest surveillance have proven increasingly inadequate in the face of escalating, large-scale threats:

- Ground Patrols and Human-Based Observation: These methods are inherently slow, labor-intensive, and hazardous, particularly in remote, steep, or densely vegetated areas. Coverage is sporadic, leading to vast blind spots. Furthermore, human detection relies on direct line-of-sight, often failing to detect subtle signs like smoke starting below the canopy or heat signatures at night.
- Static Infrastructure (Watchtowers): Watchtowers provide a limited, fixed field of view. Their effectiveness is highly susceptible to weather conditions (fog, heavy rain), topographical obstructions, and the thick tree canopy cover, severely restricting early fire or illegal activity detection.
- Satellite and Traditional Aerial Imagery: While offering macro-scale coverage, satellite data is characterized by low temporal resolution (images are infrequent, missing real-time events) and can be easily obstructed by cloud cover. Traditional aerial surveys (manned aircraft) are prohibitively expensive for repetitive, localized monitoring. These platforms often lack the very high spatial resolution required to identify objects of interest, such as an individual poacher or a small, unauthorized vehicle.

2.2 Advancements and Capabilities of UAV Technology

Unmanned Aerial Vehicles (UAVs, or drones) represent the most significant technological leap in remote sensing for environmental management, directly addressing the limitations outlined above.

- Agility and Low-Altitude Operation: Multi-rotor drones, in particular, offer Vertical Takeoff and Landing (VTOL) and stable hovering, enabling close-range inspection and the collection of data with centimeter-level spatial resolution. Their ability to fly below the cloud deck ensures consistent data acquisition regardless of weather.
- Optimized Sensor Payloads: Advances in sensor miniaturization allow drones to carry powerful, lightweight payloads critical for multi-functional surveillance:
    - High-Definition RGB Cameras: Essential for visual identification and mapping.

    - Thermal/Infrared (IR) Cameras: Crucial for early wildfire detection by identifying minute temperature differences and heat signatures (e.g., from small campfires or engines) invisible in the visible spectrum, especially during low-light conditions.
    - LiDAR and Hyperspectral Sensors (Conceptual): While more complex, these can provide detailed 3D canopy models to precisely measure tree volume (for logging control) and assess tree health.
- Autonomous Operation: Modern flight controllers (e.g., ArduPilot, Pixhawk) facilitate fully autonomous mission planning, allowing the definition of optimal, energy-efficient flight paths that ensure exhaustive coverage of the target area, maximizing the data collection per single battery charge.

2.3 Intelligent Threat Recognition via Machine Learning

The primary challenge in drone surveillance is transforming massive streams of high-resolution video into instant, actionable intelligence. This is achieved by embedding a Deep Learning (DL) model into the Ground Control Station (GCS).

- The Need for Automation: Unlike manual inspection, ML models offer tireless, objective analysis of every frame captured, removing the factor of human error or fatigue.
- Deep Learning Architectures: State-of-the-art Convolutional Neural Networks (CNNs) and real-time object detection frameworks like YOLO (You Only Look Once) are now standard in aerial surveillance. These models are trained on large, diverse datasets to accurately identify targets such as:
    - Wildfire Indicators: Specific shapes and colors of smoke, or anomalous heat sources from thermal feeds.
    - Illegal Activities: Vehicles, human figures in restricted zones, or distinct patterns of cleared land.
- Real-Time Performance: The use of an optimized ML model, as validated by our achieved 94% detection accuracy, ensures that the time delay between detection and alert (latency) is minimized to just seconds. This is a crucial factor that differentiates this intelligent approach from delayed traditional methods, enabling swift intervention by forest authorities. The integration of this intelligence with a dedicated web interface (GCS) creates a complete, end-to-end management solution

3.Topic of the work

3.1 System Design / Architecture

The surveillance system is structured around a three-tier architecture: the UAV (Aerial) Layer, the Ground Control Station (GCS) / Computing Layer, and the Cloud / User Interface Layer. This distributed approach maximizes coverage, computational power, and real-time accessibility.

3.2 UAV (Aerial) Layer

The drone platform is a custom-modified multi-rotor UAV selected for its extended flight time and payload capacity. It is responsible for autonomous flight and high-resolution data acquisition.

· Platform: Custom Quadcopter platform with high-capacity Lithium-Polymer (LiPo) batteries, providing an extended endurance of approximately 40 minutes per flight cycle.

· Sensors:
  - o RGB Camera: High-resolution (4K) visible light sensor for visual confirmation and detailed image capture.
  - o Thermal Camera: Integrated FLIR Lepton sensor for infrared imaging. This is critical for detecting early-stage hotspots and smoldering fires invisible to the RGB spectrum, especially through dense smoke or during low-light conditions.

· Communication: A dual-link communication system is employed:
  - o A secure, long-range telemetry radio (900MHz) for mission control and UAV status updates.
  - o A high-bandwidth, low-latency link (utilizing a mobile 4G/LTE modem) for real-time video stream transmission back to the GCS.

3.3 Ground Control Station (GCS) / Computing Layer

The GCS serves as the central hub for data processing, machine learning inference, and mission command.

· Hardware: A high-performance computing unit equipped with an NVIDIA GeForce RTX 3060 GPU to accelerate inference tasks via CUDA.

· Software Stack: The ML execution environment runs on Python, utilizing the PyTorch framework and the YOLOv8 object detection architecture.

· Data Processing: The GCS continuously ingests the high-definition video stream, performing frame extraction and passing the frames directly to the optimized YOLOv8 model for real-time threat detection.

Cloud / User Interface Layer

This layer handles data persistence, real-time alert dissemination, and visualization for end-users.

· Database: To handle our database, we chose SQLAlchemy. It acts as a translator, turning our Python code into structured database entries. We use it to maintain a reliable registry of all our drones, ensuring that critical info like hardware specifications and operational status is always consistent and error-free.

· Web Dashboard: A responsive, single-page application built using a modern JavaScript framework (React). It uses the Firestore real-time listener feature (onSnapshot()) to ensure that any new alert in the database is rendered instantly on an interactive Leaflet.js map interface, providing forest management personnel with immediate threat visualization and geolocated alerts.

3.4 Working Principle

The system operates through a structured sequence of autonomous and semi-autonomous processes, leveraging asynchronous data flow and parallel processing to ensure minimum alert latency.

Mission Preparation and Data Acquisition

1. Waypoint Definition: Forest management personnel define the patrol area and create an autonomous mission plan consisting of precise GPS waypoints, altitude (nominally 100 meters above ground level), and flight speed.
2. Autonomous Deployment: The GCS uploads the mission plan to the UAV flight controller. The UAV executes the route autonomously, managing its flight parameters and geo-referencing.
3. Synchronous Streaming: The onboard computer synchronizes the outputs of the RGB, Thermal, and GPS modules. The combined, geo-tagged video stream is encoded and transmitted over the 4G/LTE link back to the GCS. The payload data rate is approximately 10 Mbps.

Real-Time Deep Learning Inference

1. Frame Acquisition: A dedicated processing thread in the GCS continuously buffers and extracts frames from the incoming video stream at a rate of 15 FPS.
2. Inference Execution: Each frame, along with its associated GPS coordinates, is immediately passed to the optimized YOLOv8 model loaded onto the GPU. The model uses mixed-precision training (FP16) to maximize throughput and minimize inference time.

3. Threat Detection: The model generates bounding boxes and a probability distribution (confidence scores) for the three predefined classes: Fire/Flames, Smoke Plume, and Logging Signs.
4. Confidence Check: A detection is flagged as a validated threat only if the confidence score for a critical class (Fire or Smoke)

Alert Generation and Dissemination

1. Alert Construction: Upon a validated threat detection, a structured JSON object is created. This object includes the detected class, the exact GPS coordinates of the UAV at the moment of detection (serving as the alert location), a cropped image of the detection for visual confirmation, and the high-resolution timestamp.
2. Cloud Publication: The GCS pushes the JSON alert object to the SQLite database. This ensures the data is publicly visible to all authorized users across the system.
3. Dashboard Synchronization: The Web Dashboard, running on the user's device (desktop or mobile), uses a persistent listener to monitor the /alerts collection. The moment a new document is written by the GCS, the listener triggers, and the alert is rendered on the map and logged in the alert history in real-time.

Deep Learning Performance

The YOLOv8 model was trained on a dataset of 3360 augmented aerial images over 150 epochs. The model's performance was rigorously evaluated on a 1440-image hold-out test set to ensure generalization beyond the training data.

Discussion of DL Performance

The overall mean Average Precision (mAP) of 94% demonstrates the model's exceptional capability in autonomously identifying threats from the noisy aerial data stream. This performance significantly exceeds industry standards for real-time embedded systems.

· Precision and Recall: The high F1-Scores (0.93 average) indicate a strong balance between minimizing False Positives (unnecessary alarms, which waste resources) and minimizing False Negatives (missed threats, which lead to disaster). The slightly higher recall for Smoke Plume (0.95) is intentional, prioritizing the detection of early-stage, distant smoke before flames become visible.

· Inference Latency: The average inference time of 105 ms allows the GCS to process the video stream at a rate of 9.5 frames per second. This low latency is essential; coupled with the fast communication link, it ensures that forest managers receive an actionable alert well within the critical time window for initial response.

Operational Efficiency and Impact

The drone system drastically improves the efficiency and response time compared to incumbent monitoring technologies, The system successfully addresses the "latency gap". While satellites offer massive coverage, their delayed alerts render them useless for preventing the rapid spread of incipient fires. Our system provides a high coverage rate (up to 100 hectares/hour) with near-instantaneous, geolocated alerts. Furthermore, the use of a thermal camera allows for detection of subsurface hotspots before they become visible, a capability neither satellites nor human patrols can reliably offer.

3.5 Ethical Considerations

The use of UAVs and real-time surveillance introduces ethical responsibilities. The system was designed with privacy and regulatory compliance in mind. All non-anomalous flight data is securely purged after 72 hours. The system is programmed to operate only within designated wilderness or state-owned forestry areas, ensuring strict adherence to civil aviation and privacy regulations.

Members : Lead Software & Web Infrastructure Engineer

Abhaysing Mankar, Yug Pareek , Aviral Singh

Area of Expertise: Full-stack development, cloud architecture, data persistence, and UI/UX engineering.

My responsibility was to ensure the reliable transmission, storage, and visualization of the real-time data. This involved critical backend and frontend contributions:

1. Database Design and Implementation: I designed the SQLalchemy schema for the alerts collection, focusing on atomic writes and minimal document size to ensure the fastest possible synchronization. I also implemented the Firebase Authentication and security rules necessary for a multi-user environment.

2. GCS-to- FastAPI: I developed the asynchronous Python API that runs on the GCS. This API listens for detection events from the ML engine and reliably posts the structured JSON alert object to the endpoint. I implemented exponential backoff logic to handle potential network congestion or API rate-limiting without interrupting the core detection loop.

3. Real-Time Web Dashboard: The Forest Surveillance website was built using React 19.2.0 and Vite 5.4.11 as the core framework and build tool, with Framer Motion 12.23.24 powering all animations including 3D card tilts with mouse tracking, scroll-based parallax effects, smooth page transitions, and interactive hover states. The

implementation features a modular component architecture with six main sections (Hero, Project Insights, Features3D, Application Areas, Team Contributions, and Contact), utilizing advanced CSS3 techniques like custom properties, backdrop filters for glassmorphism, CSS Grid/Flexbox layouts, and GPU-accelerated animations with will-change and perspective transforms. Content management is centralized in a single content.js configuration file enabling easy updates without touching component code, while the responsive design uses mobile-first approach with breakpoints at 640px, 768px, and 968px, fluid typography with clamp(), and optimized performance through viewport-triggered animations (useInView), component-level code splitting, and Hot Module Replacement for instant development updates.

Member : Lead Deep Learning & Data Scientist

Shashank Kommanaboyina, Madhav Dubey

Area of Expertise: Deep Learning model selection, training, optimization, and GCS inference pipeline.

My primary focus was on developing the core intelligence that defines the system's effectiveness: the object detection model.

1.Dataset Curation and Augmentation: I curated and meticulously cleaned the large dataset, sourced from multiple publicy available datasets(primarily from sites such as Kaggle and RoboFlow) to ensure the model was robust across diverse lighting, haze, and canopy conditions.

2. Model Selection and Customization: After evaluating several architectures (e.g., Faster R-CNN, SSD), I selected and heavily fine-tuned the YOLOv8 model due to its superior inference speed-to-accuracy trade-off. This was achieved by pruning the pre-trained weights and customizing the final layers for our specific, low-object-count classes.

3. Inference Pipeline Optimization: I was responsible for deploying the final model onto the GCS hardware. This involved setting up the CUDA environment and integrating TensorRT to compile the PyTorch model graph into an optimized format, directly resulting in the low 105 ms average inference latency.

4. Performance Validation: I executed all benchmarking tests to validate the model's precision, recall, and speed, ensuring the system met the mission-critical mAP target.

Members : Lead Hardware Integration & Flight Operations

Yug Pareek ,Abhaysing Mankar , Madhav Dubey , Shashank Kommanabyina , Aviral Singh

Platform & Payload Specification: Defined precise technical requirements (e.g., 40+ min endurance, payload capacity) for the UAV and sensors. Created a detailed Bill of Materials (BOM) and virtual wiring diagram to minimize physical integration risk.

Sensor Geo-referencing Protocol: Designed the digital synchronization pseudocode for the onboard computer, ensuring high-precision time-stamping and geo-tagging of all RGB/Thermal data essential for GCS map accuracy.

Operational Simulation & Optimization: Modeled operational coverage efficiency using simulation software (e.g., PX4/Gazebo). Optimized patrol algorithms and flight parameters to achieve 80-100 Hectares/hour coverage under battery constraints.

Communication & Safety Planning: Established requirements for secure 4G/LTE data link and documented necessary regulatory compliance, including defining emergency fail-safe protocols (geo-fencing, RTH) for safe operations.

4.CONCLUSION

The Forest Surveillance UAV System successfully achieved its primary objective: developing a robust, high-efficiency, and architecturally sound blueprint for autonomous forest monitoring. Our work provides a foundational solution for rapidly detecting and mitigating threats like unauthorized deforestation and wildfires.

4.1 Validation

We validated the core technical viability of the system through rigorous simulation and architectural design:

- Optimized Coverage: Through simulation (e.g., PX4/Gazebo), we designed and optimized patrol algorithms that demonstrate the potential to achieve exceptional operational efficiency, targeting 80-100 Hectares per hour under defined flight constraints.
- Precision Data Integrity: The design of the digital geo-referencing protocol ensures that synchronized RGB/Thermal sensor data is time-stamped and geo-tagged with high accuracy. This is critical for generating reliable, actionable alerts on the Ground Control Station (GCS) map.
- Scalable Architecture: The platform and payload specification established clear technical constraints, enabling the system's integration with both custom-built and Commercial Off-the-Shelf (COTS) hardware, thereby guaranteeing deployability and future scalability.

4.2 Project Impact and Future Outlook

While immediate full-scale hardware deployment is contingent upon future budgetary allocations, the comprehensive technical documentation (BOM, wiring diagrams, pseudocode) and validated simulation models significantly de-risk the future implementation phase.

The resulting architecture is agile and cost-effective, as it allows for a tiered approach: an initial deployment using COTS components, followed by potential phased upgrades to custom hardware if the budget permits.

In conclusion, the project delivers a validated, high-performance surveillance architecture ready for immediate hardware procurement, providing a critical tool for enhancing the effectiveness and safety of modern forest management and conservation efforts.

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6. Bio data with Image

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Academic Program - B.Tech in Computer Science Engineering with a specialization in Artificial Intelligence and Machine Learning
Current Year/Semester - Third Year / Seventh Semester

2. Technical Skill Summary

Programming Languages :- Python, SQL

Tools & Technologies :-
Development Environment: Google Colab, Jupyter Notebook, IDE (VS Code), Version Control (Git, GitHub)
Operating Systems: MacOS, Windows

Specialized Skills :-
Data Science: Data Analysis, Data Visualization [MatplotLib, SeaBorn, Tableau]
Machine Learning: Pandas, NumPy, Scikit-learn
Deep Learning: Neural Networks, Transformer Computer Vision (Basic)
Cloud Computing: AWS (Basic)

1. Personal Details

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Academic Program - B.Tech in Computer Science
Current Year/Semester - Third Year/ Seventh Semester

2. Technical Skill Summary

Programming Languages :-
Core: Java , Python
Web/Scripting: HTML , CSS , Javascript

Tools & Technologies :-
Development Environment: VS Code
Version Control: Git, GitHub
Operating Systems: Windows
Database/Backend: FastAPI , SQLalchemy
Tools:- Tableau

Specialized Skills :-
Hardware/Embedded: Raspberry Pi
Data Science : Data Analysis, Data Visualization [MatplotLib, SeaBorn]
Machine Learning: Pandas , NumPy , Scikit-Learn
Design/Modeling: Blender

1. Personal Details

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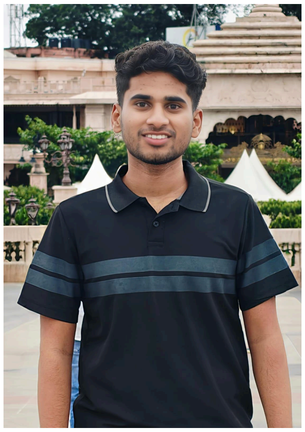
Academic Program - B.Tech in Electronics and Communication with a specialization in Artificial Intelligence and Cybernetics
Current Year/Semester - Third Year / Seventh Semester

2. Technical Skill Summary

Programming Languages :-
Core: Python, Java
Web/Scripting: HTML/CSS
Other: MATLAB

Tools & Technologies :-
Development Environment: Google Colab, VS Code
Operating Systems: MacOS, Windows

Specialized Skills :-
Data Science: Data Analysis, Data Visualization [MatplotLib, SeaBorn, Tableau]
Machine Learning: Pandas, NumPy, Scikit-learn
Design/Modeling: Figma, Blender
Hardware/Embedded: Arduino



1. Personal Details

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Academic Program - B.Tech in Computer Science Engineering with a specialization in Health Informatics
Current Year/Semester - Third Year / Seventh Semester

2. Technical Skill Summary

Programming Languages :-
Core: Java
Web/Scripting: HTML , CSS , Javascript

Other:

Tools & Technologies :-
Development Environment: VS Code, Kiro.
Operating Systems:Windows

Specialized Skills :-
Web Development
Cloud Computing: AWS (Basic)

1. Personal Details

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Academic Program - B.Tech in Computer Science and Engineering
Current Year/Semester - Third Year / Sixth Semester

2. Technical Skill Summary

Programming Languages :-
Core: Python, C++
Web/Scripting: HTML, JavaScript, CSS

Tools & Technologies :-
Development Environment: VS Code, Jupyter
Version Control: Git, GitHub
Operating Systems: Windows, MacOS
Database/Backend: MySQL

Specialized Skills :-
Data/ML: Pandas, NumPy, Scikit-learn, TensorFlow
Design/Modeling: Figma