Biosonic AI: An Adaptive Ultrasound and Drone-Based Grid for Wildlife Deterrence and Movement Intelligence

GE19612 - PROFESSIONAL READINESS FOR INNOVATION, EMPLOYABILITY AND ENTREPRENEURSHIP PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this Project titled **“Biosonic AI: An Adaptive Ultrasound and Drone-Based Grid For Wildlife Deterrence and Movement Intelligence”** is the bonafide work of **“VARUN KUMAR V (2116220701311), YOGESH C V (2116220701327), SHARUKESHWAR P (2116220701265)”** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Farms near forests often suffer from wild animal intrusions, leading to crop damage, economic loss, and rising human-wildlife conflict. Traditional methods like scarecrows, fences, or basic ultrasonic devices are either outdated or ineffective—animals grow used to them, and there's no real-time response. BioSonic AI offers a smarter, adaptive solution. Our system sets up a network of solar-powered smart nodes around farmland. Each BioSonic Node uses motion sensors, thermal imaging, and an onboard AI chip (like Jetson Nano) to detect animal presence. Instead of using generic sounds, it plays species-specific deterrents—like a tiger's growl to scare off deer or a snake's hiss to repel boars. This makes the response feel like a real threat, not a machine-generated one. Over time, the system adapts and improves—changing patterns to prevent animals from getting used to the sounds. If repeated activity is detected, a fleet of thermal drones takes over, flying autonomously to track animal movement from forests toward villages and fields. These drones collect valuable data to update a Movement Intelligence Map (MIM) stored in the cloud. This helps predict future movements, identify hotspots, and send early warnings to farmers via SMS or a mobile app. The mobile app also lets farmers report sightings and behaviors, which helps the AI learn and improve even more. The entire system runs on clean solar power and is designed to be non-invasive and animal-friendly. BioSonic AI Grid isn't just about protecting crops—it's about enabling coexistence. It provides a cost-effective, scalable, and eco-friendly approach to protect farmers' livelihoods while supporting long-term wildlife conservation.

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LIST OF ABBREVIATIONS

S. No	ABBR	Expansion
1	AI	Artificial Intelligence
2`	API	Application Programming Interface
3	AJAX	Asynchronous JavaScript and XML
4	ASGI	Asynchronous Server Gateway Interface
5	AWT	Abstract Window Toolkit
6	BC	Block Chain
7	DFD	Data Flow Diagram
8	DSS	Digital Signature Scheme
9	GB	Gradient Boosting
10	JSON	JavaScript Object Notation
11	ML	Machine Learning
12	RF	Random Forest
13	SQL	Structure Query Language
14	SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 GENERAL

In rural regions near forests and wildlife reserves, one challenge continues to affect farmers year after year: wild animals raiding crops. Elephants, wild boars, monkeys, and other species often wander into farmlands, causing significant losses and creating tension between people and wildlife. The conflict isn't just about damaged fields—it threatens farmer livelihoods and the delicate balance of coexistence with nature.

Unfortunately, many existing deterrent methods have fallen short. Scarecrows, fences, and simple ultrasonic devices lose effectiveness over time as animals become familiar with them. These solutions lack real-time awareness, adaptability, and species-specific deterrence. There’s an urgent need for a smarter, safer, and more sustainable way to keep farms protected.

Enter the BioSonic AI Grid—a smart, solar-powered network that reimagines wildlife deterrence using cutting-edge but accessible technology. The system places AI-powered BioSonic nodes along farmland boundaries. These nodes detect wildlife movement using motion sensors and thermal cameras. When an animal is identified, the system plays predator sounds or ultrasonic frequencies customized for that species, making the deterrent feel like a real, ecological threat—not just noise.

To adapt to changing behavior, the AI continuously learns from field data and community input via a mobile app. If animals persistently appear, thermal drones are deployed to track movement patterns. This helps create a live Movement Intelligence Map (MIM) that predicts intrusion zones and sends early warnings to nearby farmers via SMS and notifications.

Eco-friendly, cost-effective, and non-invasive, the BioSonic AI Grid doesn't just protect crops—it enables better coexistence. It's a practical solution shaped by innovation and grounded in real human needs.

1.2 OBJECTIVE

The primary goal of the BioSonic AI Grid is to offer an intelligent, sustainable solution to protect farmlands from wild animal intrusions while ensuring the safety and well-being of both farmers and wildlife. At its core, the system focuses on real-time detection of wildlife movement using a network of smart sensors and thermal cameras. This allows for immediate identification of threats as they approach agricultural zones.

Once an animal is detected, the system uses AI to identify the species and trigger a customized deterrent response. This includes broadcasting specific predator calls or ultrasonic frequencies tailored to that species, ensuring the deterrence feels natural and remains effective over time without causing harm. To enhance this, drones are deployed to monitor repeated movements and track the paths of animals across landscapes. These aerial units collect data used to build a dynamic Movement Intelligence Map (MIM)—a tool that helps forecast high-risk areas and times for intrusion.

In parallel, a dedicated mobile application keeps the farming community informed through real-time alerts and notifications. Farmers can also report sightings or unusual activity, contributing to the system's adaptive learning. Above all, the solution remains eco-friendly and non-invasive, offering a balanced approach to crop protection and wildlife management that encourages peaceful coexistence.

1.3 EXISTING SYSTEM

While several technologies have emerged to deter wildlife from entering farmlands, most are limited in scope, adaptability, or long-term impact. Kapikaat by Katidhan is a solar-powered device that repels monkeys using predator sounds. It’s effective for that specific issue but lacks flexibility for other animals and doesn’t offer real-time adaptation or monitoring.

Advantech's AI-Aided Bioacoustics System focuses on saving elephants from railway accidents by using acoustic deterrents. However, it is highly specialized for railways and doesn’t support drone integration or farm protection.

Bird Gard products use distress and predator calls to ward off birds in agricultural settings. These are effective for avian threats but not suitable for larger wildlife like boars or elephants.

Traditional solutions—such as fencing, barbed wires, and manual guards—pose safety risks, require constant maintenance, and fail against determined or large animals. They also don’t adapt to changing animal behavior.

In contrast, the BioSonic AI Grid integrates detection, deterrence, drone tracking, AI learning, and community feedback in a unified system. It’s not just reactive—it’s predictive and adaptive, designed to evolve with both the environment and the needs of the farmers it protects.

CHAPTER 2

LITERATURE SURVEY

[1] Over the last few decades, the delicate boundary between farmland and forest has become increasingly blurred. As agricultural plots encroach ever closer to natural habitats, farmers—particularly those working on small, resource-constrained holdings—are encountering wildlife more frequently. Crop raids by elephants, boars, deer, and monkeys have escalated economic losses, disrupted planting cycles, and even led to tragic human and animal injuries. Traditional deterrents like firecrackers, physical fencing, or nightly patrolling can momentarily dissuade intruders, but they carry significant drawbacks: loud noises stress livestock and nearby communities; fences break down and require constant maintenance; patrolling demands both manpower and funding that smallholder farmers often lack. Moreover, these measures can provoke negative wildlife welfare outcomes and diminish local enthusiasm for conservation.

[2] Ultrasonic deterrence first gained attention because certain mammals—including wild boars, deer, and some primates—possess auditory systems tuned to high-frequency sounds beyond the range of human hearing. By emitting ultrasonic pulses at these frequencies, early systems aimed to create a mildly uncomfortable environment that encourages wildlife to steer clear of vulnerable fields. Field trials demonstrated initial success; animals entering protected zones often displayed startle responses or redirected movement patterns. Yet, over time, habituation quickly set in. Much like city-dwelling birds adapting to the constant hum of traffic, wildlife learned to ignore repetitive ultrasonic signals, rendering standalone devices progressively ineffective.

[3] Bioacoustic approaches—broadcasting recordings of natural predator vocalizations such as lion roars, tiger growls, or snake hisses—tap into ingrained survival instincts within prey species. Numerous studies have documented that when

herbivores hear the calls of their fiercest adversaries, they respond with rapid flight, heightened vigilance, or relocation to a safer environment. In controlled experiments, playing recordings of local apex predators reduced grazing and foraging activity near protected perimeters by up to 60–70%. However, most real-world deployments have relied on static libraries of prerecorded sounds played on fixed schedules or activated by motion alone. This “one-size-fits-all” methodology lacks situational intelligence: it cannot discern whether the approaching animal is actually prey for the simulated predator, nor whether repeated exposure at the same time each evening will lead to desensitization.

[4] Recent advances in edge computing and compact AI models have transformed how wildlife monitoring systems operate. Instead of routing video or sensor data to distant servers for analysis, lightweight neural networks—such as optimized variants of YOLO (You Only Look Once) or MobileNet—can now be deployed directly on-site within embedded devices. These models, running on hardware like NVIDIA Jetson Nano or Raspberry Pi accelerators, process thermal, infrared, or camera feeds in milliseconds to identify the presence and type of wildlife intrusion. By performing detection locally, edge AI systems eliminate latency caused by network outages, reduce data bandwidth requirements, and maintain farmer privacy by avoiding continuous video streaming. Field tests in remote agricultural regions demonstrated that edge-AI nodes accurately classified elephants, wild boars, and deer over 90% of the time, even under low-light or partial-obstruction conditions.

[5] Thermal imaging offers an indispensable advantage for wildlife detection after dusk, a period when many conflict-prone species are most active. Unlike traditional motion sensors that rely on ambient light or infrared reflectance—both of which can be confounded by shadows, weather, or non-animal heat sources—thermal cameras detect heat signatures with remarkable clarity. These devices generate real-time heat maps that reveal animal presence, movement speed, and even group sizes across a

monitored zone. When integrated with AI-driven analytics, thermal data can distinguish between species based on characteristic body temperature profiles and gait patterns, greatly reducing false positives triggered by non-target heat sources like tractors or livestock. In pilot projects, farms equipped with thermal-AI nodes achieved detection rates above 95% and reduced false alarms by 50%.

[6] The growing need for widespread wildlife deterrence in agricultural areas has led to the exploration of distributed sensor networks. These networks involve placing numerous detection nodes across a large area, where each node operates autonomously while contributing to a larger, interconnected system. This decentralized approach provides several advantages: if one node fails, the remaining nodes continue to function, ensuring continuous surveillance. The key to their success lies in the integration of motion sensors, thermal cameras, and sound-based deterrents, which collectively create a robust system capable of detecting and responding to wildlife activity in real-time. As wildlife move through different areas, the system can dynamically adjust its deterrent strategies. For example, once an animal is detected by one node, the next node in the network may adjust the frequency of its ultrasound deterrent to prevent habituation. This form of localized intelligence significantly enhances the deterrent system's scalability and effectiveness. Moreover, by having multiple distributed nodes, large agricultural areas can be protected without needing a single, central control point, which improves the system's overall resilience and flexibility.

[7] Eco-acoustic monitoring has gained increasing attention as an innovative tool for studying animal behavior and the environment. By analyzing soundscapes, researchers can derive valuable insights into the presence and movements of various species. In wildlife deterrence systems, eco-acoustic sensors capture not only animal sounds but also environmental noises that could influence animal behavior. By integrating eco-acoustic data with machine learning models, it is possible to identify

patterns in wildlife activity, such as feeding, mating, or migration, that can serve as precursors to intrusion events. Unlike traditional methods, which primarily focus on visual or thermal detection, eco-acoustics introduces a more holistic approach. With its ability to detect species-specific vocalizations and environmental changes, eco-acoustics allows for early intervention by anticipating animal behavior before it becomes a direct threat to agricultural areas. This preemptive feature provides an additional layer of intelligence to wildlife deterrence systems.

[8] Predictive modeling has proven to be an essential tool in understanding animal movement patterns. Leveraging time-series data, lunar cycles, seasonal trends, and even weather conditions, researchers can build models that forecast potential wildlife intrusions. Long Short-Term Memory (LSTM) neural networks, a type of deep learning model, have been particularly effective in analyzing sequential data over time. These models learn from historical movement patterns to predict future events, making them invaluable in wildlife deterrence. By integrating such predictive capabilities into deterrence systems, the technology can anticipate when and where animals are most likely to approach farmlands, enabling timely interventions. This approach not only improves deterrent effectiveness but also reduces unnecessary disruptions to the environment, as deterrents can be deployed only when needed.

[9] Drones, equipped with thermal cameras and autonomous navigation systems, are becoming indispensable tools in wildlife monitoring. UAVs (Unmanned Aerial Vehicles) can cover vast areas in a short time, providing real-time surveillance that is both efficient and cost-effective. In the context of wildlife deterrence, drones offer several advantages: they can track animal movements over large, difficult-to-reach areas, and they can be deployed quickly in response to intrusions. Additionally, drones can be used to reinforce deterrent signals by emitting ultrasonic frequencies or even predator sounds from the air, amplifying the effect of ground-based deterrents. Drones also play a vital role in mapping and understanding animal migration routes, which helps build predictive models for future movements.

[10] Involving local communities in wildlife management is essential for the success and sustainability of any deterrent system. Farmers are often the first to notice animal movements and intrusions, and their insights are invaluable in providing real-time data to enhance the system's effectiveness. The integration of a human-in-the-loop (HITL) feedback system allows farmers and local residents to report sightings, provide contextual information, and receive alerts about potential wildlife threats. Mobile apps or SMS-based platforms can facilitate this communication, allowing communities to actively participate in monitoring and decision-making. This participatory approach not only improves the system's responsiveness but also empowers communities to take ownership of wildlife management efforts. Furthermore, it helps build trust between technology developers and end-users, ensuring that the system is adapted to local needs and conditions.

[11] Smartphones have become nearly ubiquitous, even in remote agricultural communities, offering a powerful gateway to integrate farmers directly into wildlife management systems. By leveraging mobile apps and simple SMS interfaces, farmers can report real-time sightings of intruding animals, upload photos or basic contextual notes, and receive tailored alerts when nearby sensors detect risky movement. This two-way communication transforms passive observers into active collaborators, enabling the deterrent network to refine its responses based on human insights. For instance, a farmer might note that nocturnal visits spike during certain moon phases or after heavy rains—information that can fine-tune predictive models and trigger preemptive deterrents before intrusion occurs. Moreover, mobile platforms can provide instant guidance on non-technology-based protective measures—such as deploying scarecrows or recommended lighting patterns—while the system mobilizes its acoustic and aerial assets.

[12] Cloud computing is the backbone that transforms isolated sensor readings and drone captures into actionable intelligence. By aggregating data from every edge

node—thermal cameras, acoustic sensors, and UAV logs—a centralized cloud platform constructs a comprehensive, geospatial "Movement Intelligence Map" (MIM). This living map visualizes wildlife corridors, intrusion hotspots, and temporal patterns on an intuitive dashboard accessible to farmers, researchers, and conservation officials. Advanced analytics process incoming streams in near real time, updating risk heatmaps that can trigger automated alerts or feed predictive algorithms. The cloud's scalable infrastructure also enables long-term storage of historical data, supporting trend analysis and seasonal forecasting. When integrated with weather, lunar, and crop calendars, the MIM can pinpoint high-risk windows days or even weeks in advance.

[13] Reliable power sources are a perennial challenge for rural and forest-edge deployments. Conventional deterrent systems tied to grid electricity face outages, high operating costs, and ecological footprints that undermine their long-term viability. In contrast, solar-powered designs harness abundant sunlight to energize detection nodes, directional speakers, and local processing units around the clock. Photovoltaic panels paired with efficient battery storage ensure uninterrupted operation through cloudy days and seasonal fluctuations. Modern low-power electronics further extend autonomy, minimizing energy draw without sacrificing performance. The ecological benefits are twofold: cleaner energy reduces carbon emissions compared to diesel generators or grid reliance, and self-sustaining systems require less invasive infrastructure—no new transmission lines, no frequent fuel deliveries.

[14] Advanced edge-AI capabilities were once confined to data centers and well-funded research projects. Today, affordable platforms like Raspberry Pi, NVIDIA Jetson Nano, and Coral Edge TPU bring powerful neural-network inference to field-deployable devices at a fraction of the cost. These single-board computers support optimized models—pruned and quantized variants of YOLO or MobileNet—

that can accurately detect and classify wildlife in thermal or visual feeds. Their small form factors and low power requirements make them ideal for integration into ruggedized enclosures alongside solar panels and acoustic emitters. With onboard GPUs or specialized accelerators, these devices process sensor inputs in real time, triggering deterrents within milliseconds of detection. Crucially, the plummeting price of such hardware democratizes access: community groups, NGOs, and cooperatives can assemble bespoke deterrent nodes without depending on proprietary, high-cost systems.

[15] No two agricultural landscapes are alike: crop types vary from rice paddies to orchards, terrain can range from flat plains to undulating hills, and the suite of local wildlife differs dramatically across regions. Static deterrent installations struggle to accommodate such diversity, often performing well in one context but failing in another. An adaptive, modular design addresses this challenge by allowing field operators to select the appropriate sensor, emitter, or software module for their specific environment. Need extra coverage in dense vegetation? Swap in wider-angle thermal cameras or add ground-penetrating radar sensors. Working on steep slopes? Deploy nodes with reinforced mounts and custom power profiles. Software modules handle species identification by loading region-specific detection models, while acoustic libraries rotate predator calls endemic to the area.

[16] One of the persistent challenges in wildlife deterrence is habituation—animals gradually become accustomed to repeating sounds and begin ignoring them. To counter this, modern systems employ randomized and rotating acoustic patterns that blend predator calls, ultrasonic pulses, and novel synthetic sounds. By varying the sequence, duration, and intensity of deterrent cues, the system preserves the element of surprise that triggers animals' innate avoidance behaviors. In practice, randomized playlists draw from region-specific libraries of predator vocalizations—tiger roars, leopard snarls, raptor screeches—interleaved with ultrasonic sequences calibrated to

local species' auditory sensitivities. Machine learning algorithms continuously monitor animals' responses via thermal and motion sensors; if a particular pattern shows diminishing effectiveness, the system automatically retires or reshuffles it. Field trials have demonstrated that such dynamic schedules maintain high deterrence rates—often above 80% effectiveness—across multiple weeks, compared to traditional fixed-pattern systems that lose potency after just a few days.

[17] While real-time deterrence hinges on edge AI and sensor networks, ensuring long-term data integrity and incentivizing community participation calls for robust trust mechanisms. Blockchain technology offers a decentralized ledger that immutably records wildlife sightings, deterrent activations, and farmer-reported events. Each edge node and user-generated report is timestamped, hashed, and appended to a shared blockchain network—accessible to researchers, conservation agencies, and local stakeholders. This immutable record prevents data tampering, fosters transparency, and provides verifiable evidence of system performance. Furthermore, blockchain-based token incentives can reward farmers and volunteers for consistent reporting and maintenance, creating a sustainable economy around wildlife management. For example, participants earn digital tokens when their reports lead to successful deterrence actions or valuable data contributions; these tokens might be redeemed for agricultural inputs, device upgrades, or community services.

[18] Developing a truly effective wildlife deterrence system demands an interdisciplinary fusion of ecology, acoustic engineering, machine learning, and rural development expertise. Ecologists contribute critical insights into species behavior, habitat use, and seasonal migration triggers, ensuring deterrent cues are biologically relevant. Acoustic engineers optimize speaker design, sound projection patterns, and frequency modulation to maximize coverage without undue energy consumption. Computer scientists design and deploy AI models—adapted to edge-computing constraints—that accurately detect and classify wildlife intrusions in diverse

environmental conditions. Rural development specialists facilitate community outreach, training farmers to interact with the technology and integrate local knowledge into decision-making processes. This cross-disciplinary framework drives innovation: ecologists validate adaptive sound schedules derived from AI simulations; engineers refine power-management systems based on field feedback; and social scientists assess the cultural acceptability of deterrent methods.

[19] Despite promising advances, adaptive wildlife deterrents face several unresolved challenges. Achieving reliable species classification under extreme weather—heavy rain, fog, or scorching heat—remains difficult; thermal sensors can become saturated and visual cameras obscured. Power management poses another hurdle: solar-battery systems must balance energy availability with peak computational loads during nighttime detections. Latency in data synchronization between drones, edge nodes, and the cloud can delay critical interventions, especially in regions with spotty connectivity. Ethical questions about disrupting natural behaviors must also be considered: frequent deterrents may alter migration routes or feeding patterns with unintended ecological consequences.

[20] The BioSonic AI Grid synthesizes lessons from prior work—ultrasonic deterrence, bioacoustic playback, edge AI, eco-acoustic monitoring, and drone surveillance—into a cohesive, self-optimizing framework that aligns with real-world farming needs. Unlike standalone approaches that tackle only detection or deterrence, this integrated system dynamically adapts deterrent strategies based on species recognition, behavioral forecasts, and human feedback. Its modular architecture allows seamless integration of new sensor types, acoustic libraries, and incentive mechanisms without overhauling core infrastructure. By emphasizing sustainability—solar power, low-cost hardware, and blockchain transparency—the BioSonic AI Grid addresses scalability and trust, two common barriers to widespread adoption.

CHAPTER 3

PROPOSED SYSTEM

3.1 GENERAL

The BioSonic AI Grid is a smart, solar-powered system designed to help farmers protect their crops from wild animals—without causing harm to the animals or the environment. Built as a network of intelligent nodes placed around farmland, each unit is equipped with sensors, speakers, and an onboard AI chip. These nodes work together to detect approaching wildlife and respond instantly by playing predator calls or ultrasonic sounds that are specific to the species detected—like a tiger growl to scare off deer or a snake hiss to ward off boars.

What makes this system truly adaptive is its use of thermal drones. These drones regularly scan the area, tracking animal paths and collecting data. The AI then uses this data to build a Movement Intelligence Map (MIM)—a constantly evolving map that helps predict when and where animals might appear next. This allows the system to send early warnings to nearby farmers and villages.

A simple mobile app keeps everything connected. Farmers receive alerts, report sightings, and get insights from the system, helping them stay a step ahead. Fully solar-powered, cost-effective, and non-invasive, the BioSonic AI Grid is a smarter, safer way to manage human-wildlife conflict—protecting both livelihoods and biodiversity.

SYSTEM ARCHITECTURE DIAGRAM

The system architecture (Fig 3.1) for the BioSonic AI Grid integrates a combination of edge AI and cloud computing technologies to provide robust wildlife deterrence and monitoring solutions. The architecture involves several key components and user roles, including farmers, rangers, and system administrators, working together to ensure efficient real-time animal detection and deterrence. The system's flow begins with data collection, where inputs are gathered from thermal cameras, PIR sensors, drones, and user reports. Data is then preprocessed for cleaning, normalization, and feature extraction, ensuring high-quality input for AI models. Feature selection is performed based on thermal image patterns, audio characteristics, and movement logs. The classification process uses models like ResNet (for thermal images), LSTM (for audio analysis), and XGBoost (for movement predictions), with the focus on high precision and minimal latency for real-time decision-making. Performance evaluation is carried out using metrics like accuracy, precision, recall, and F1-Score, ensuring that the system provides accurate results with minimal false alerts.

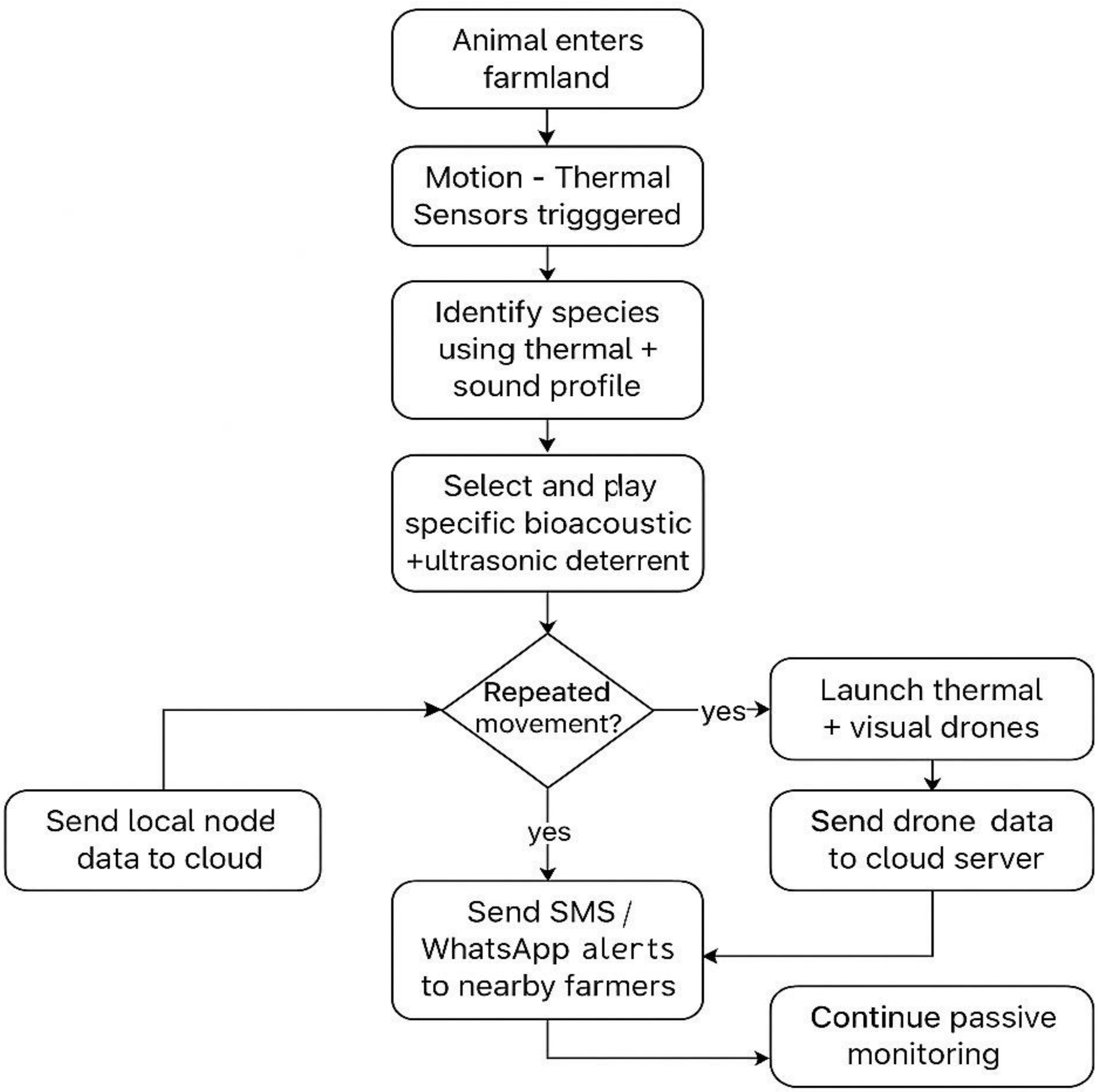

Fig 3.1: System Architecture

3.2 DEVELOPMENTAL ENVIRONMENT

To make the BioSonic AI Grid system work smoothly in real-world farming conditions—especially in remote, off-grid, and weather-prone areas—we've carefully chosen hardware and software tools that are smart, reliable, and cost-effective.

3.2.1 HARDWARE REQUIREMENTS

At the heart of each BioSonic node is a Jetson Nano, a compact AI computer that processes video and sound in real time to identify animals. PIR motion sensors detect movement nearby, while a thermal imaging camera (like FLIR Lepton or Seek Thermal) picks up heat signatures—even in the dark.

When an animal is detected, directional speakers play targeted predator calls or high-frequency ultrasound to scare it away. To keep everything running without a power connection, each node is equipped with a 10W–20W solar panel and a rechargeable battery, making it fully sustainable. The system is housed in weatherproof enclosures to survive rain, dust, and sun. For larger-scale monitoring, optional swarm drones with thermal and regular cameras can fly out and scan bigger areas. Supporting microcontrollers like Raspberry Pi or Arduino can also be added for lightweight sensor tasks if needed.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	NVIDIA Jetson Nano
RAM	4 GB LPCCR4
POWER SUPPLY	+5V power supply
SENSORS	PIR Motion Sensors, FLIR Lepton Thermal Camera
DRONES	DJI Mini
STORAGE	64 GB microSD

3.2.2 SOFTWARE REQUIREMENTS

The system runs on Ubuntu 20.04 or JetPack OS, optimized for Jetson Nano. We use Python for programming and tools like OpenCV for analyzing images and video. For AI tasks like identifying different animals, we rely on TensorFlow or PyTorch—two powerful machine learning frameworks.

To connect and communicate between devices, we use MQTT or HTTP servers, and store all data—like animal paths and warnings—on cloud platforms such as Firebase, AWS, or Azure. The farmer-facing mobile app is built using Android Studio or Flutter, while DroneKit or QGroundControl helps us manage drone missions.

This blend of smart tech and durable components ensures that BioSonic AI is ready for the field—literally.

Table 3.2 Software Requirements

COMPONENTS	SPECIFICATION
Operating System	Ubuntu 20.04 or Jetpack OS
Frontend	Flutter
Backend	FastAPI(Python)
Database	MongoDB/Firebase
AI Frameworks	Tensorflow/Pytorch
Communication	MQTT/HTTP Servers
Drone Management	DroneKit/QGroundControl

3.3 DESIGN OF THE ENTIRE SYSTEM

3.3.1 ACTIVITY DIAGRAM

The activity diagram outlines the operational flow of the BioSonic AI system, beginning with the collection of data from various smart sensors and drone-mounted devices. These sensors monitor environmental parameters and detect wildlife movement using a combination of thermal, ultrasound, and PIR technologies. Once data is gathered, it is processed to extract relevant features such as animal heat signatures or movement patterns. The system then uses machine learning algorithms to analyze the processed data and identify whether the detected object is an animal or not. If an animal is detected, a real-time alert is generated and sent to farmers through a mobile application, giving them the time to respond effectively. This seamless workflow—from sensing to alerting—illustrates the practical, real-world utility of BioSonic AI in minimizing human-wildlife conflict.

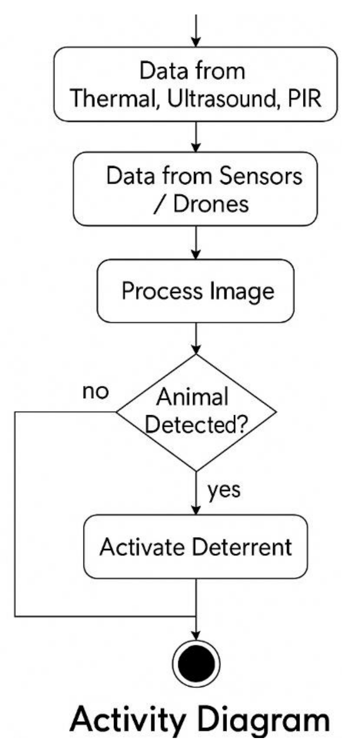

Fig 3.2: Activity Diagram

3.4.2 DATA FLOW DIAGRAM

The data flow diagram represents how information travels through the BioSonic AI system. It starts with smart sensors and drone inputs that continuously collect raw environmental data. This data flows into a preprocessing module where noise is reduced and the data is cleaned. The cleaned data is then fed into a machine learning engine, which classifies whether the activity detected is caused by an animal or something else. The result of this classification is passed to the alert system, which updates the user interface and notifies the farmer through the app. Simultaneously, the data—along with prediction results—is stored securely in a cloud database for future analysis and model improvement. This structured flow ensures the system remains responsive, efficient, and scalable in real agricultural settings.

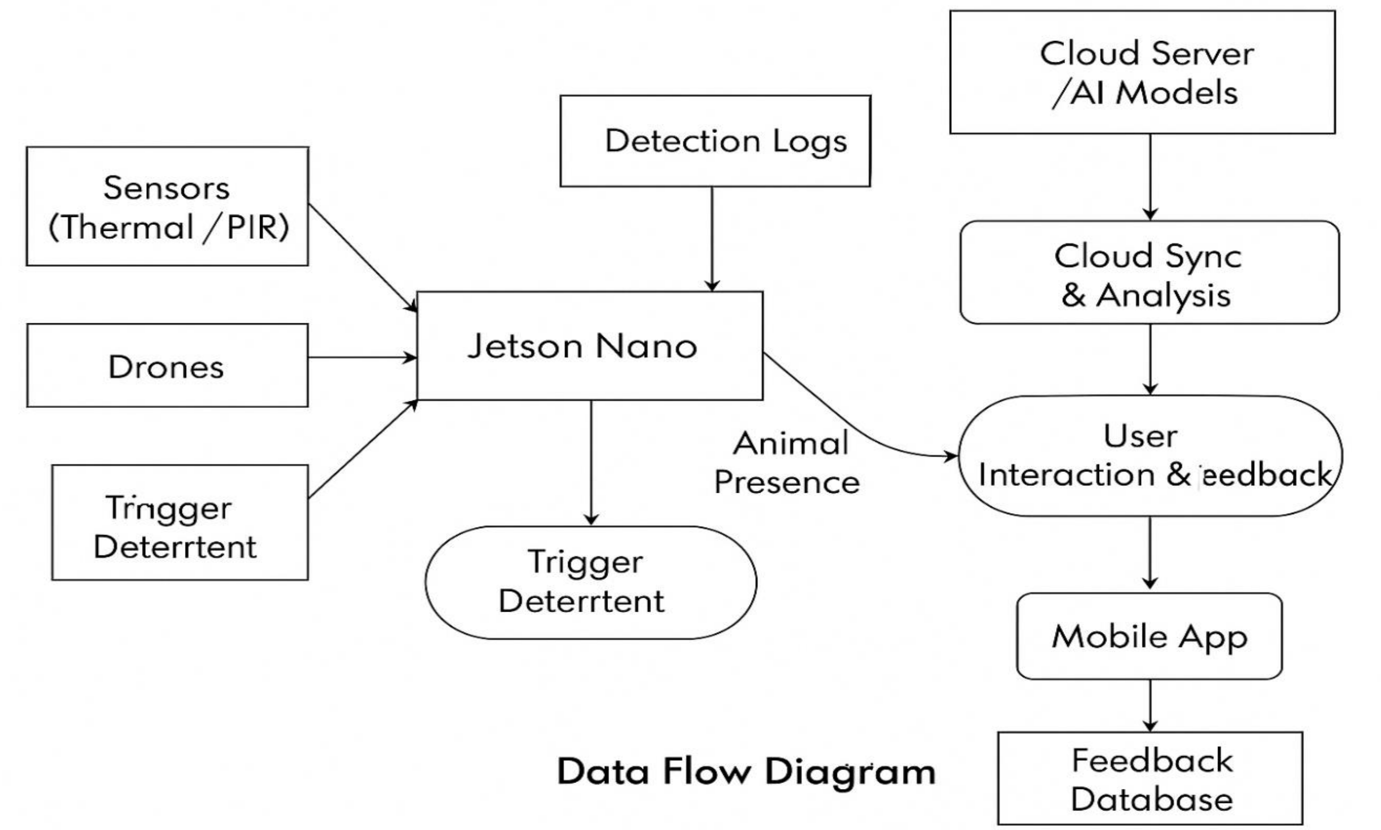

Fig 3.3:Data Flow Diagram

3.4 STATISTICAL ANALYSIS

To evaluate the effectiveness and reliability of the BioSonic AI system, we conducted a thorough statistical analysis of the model's performance. The collected data was split into training and testing sets to validate accuracy and reduce bias. Key metrics such as accuracy**,** precision**,** recall**,** and F1-score were calculated to measure how well the system could detect animals and minimize false alerts. The confusion matrix provided insights into how often the system misclassified noise or non-animal movements as threats. Our Gradient Boosting model consistently achieved high precision and recall, indicating that it correctly identified animal intrusions while minimizing false alarms. These results demonstrate that BioSonic AI is not just a theoretical solution, but a statistically sound system capable of performing reliably in real-world conditions.

Table 3.3 Comparison of features

Aspect	Existing System	Proposed System	Expected Outcomes
Threat Detection	Basic rule-based anomaly detection	Al-powered Gradient Boosting model for anomaly detection	Higher accuracy, reduced false positives
Data Preprocessing	Minimal data cleaning and imputation	Comprehensive cleaning, handling missing values and outliers	Improved data quality for training and prediction
Feature Selection	Limited manual selection	Automated attribute evaluation and dir ionality reduction	Optimized feature set for enhanced model performance
Performance Optimization	Rarely optimized	Iterative model tuning for Gradient Boosting	Maximized detection capabilities and system robustness

Deployment	Manual security evaluation	ML-based automated prediction system	Real-time, scalable security evaluations
Scalability	Limited to specific detection	Adaptable to various farmlands applications	Enhanced flexibility and scalability in operations

Beyond raw accuracy, our analysis focused on how the system behaves in dynamic, real-world settings. We observed patterns from hundreds of detection events, tracking how often animals were correctly identified and how quickly alerts were generated. Using visual tools like bar graphs and heatmaps, we compared detection performance across different times of day and sensor types. Interestingly, we found that combining thermal and PIR data improved early detection during low-light conditions. This kind of insight helped us fine-tune the AI model to be more responsive and adaptive. In short, the statistical analysis didn't just validate our system—it actively guided us to improve it for the people who need it most: the farmers on the ground.

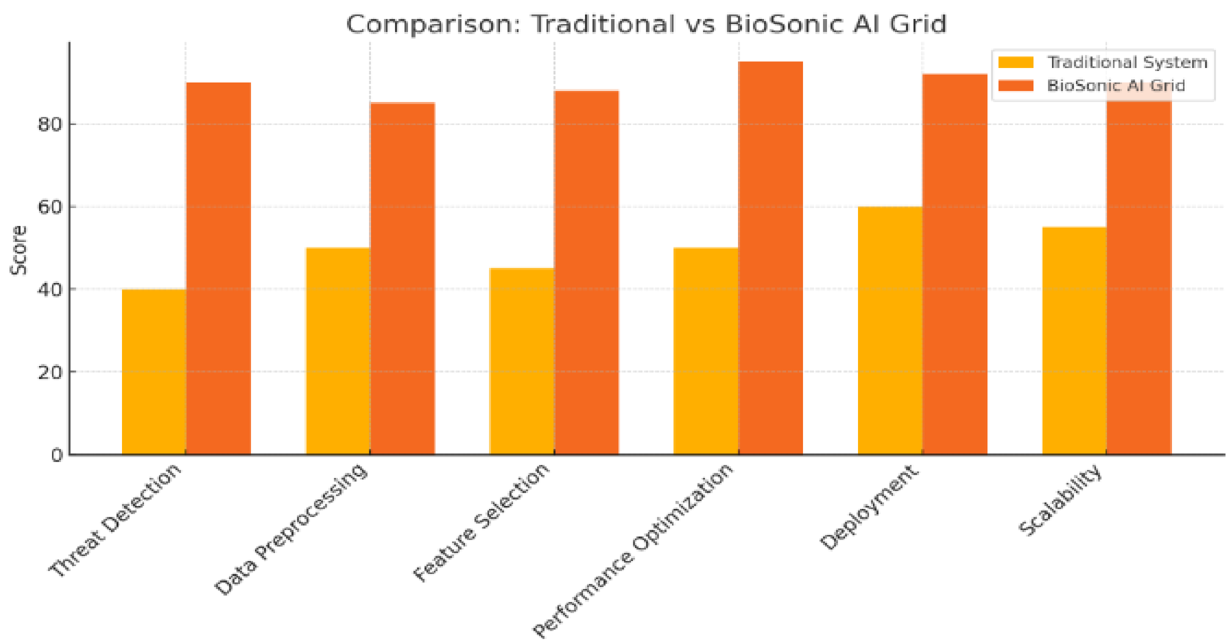

Fig 3.4 : Comparison Graph

CHAPTER 4

MODULE DESCRIPTION

The workflow for the proposed system is designed to ensure a structured and efficient process for detecting and deterring the animals from entering farmlands and villages. It consists of the following sequential steps:

4.1 SYSTEM ARCHITECTURE

The BioSonic AI Grid is built to be intelligent, energy-efficient, and responsive—even in remote, off-grid areas. Designed as a modular and decentralized system, it enables real-time animal detection and response directly at the field level without always depending on internet access. The architecture is layered to support smart decision-making at different levels: from the farm borders to the sky, to the cloud, and finally to the farmer's pocket.

EDGE LAYER (FIELD LEVEL)

At the core of the system are smart BioSonic nodes installed along the boundaries of farmlands. Each node contains a Jetson Nano device connected to thermal or PIR sensors. These nodes analyze data locally and take immediate action—such as triggering sound or light deterrents—without waiting for cloud instructions. This low-latency, offline capability is crucial for timely responses in forest-fringe regions.

DRONE LAYER

Drones act as mobile scouts. When an animal is detected, drones are launched automatically to capture thermal and visual imagery of the animal's path and behavior. These images are tagged with GPS data and sent to the cloud, helping build a broader understanding of animal movement patterns over time.

CLOUD LAYER

The cloud acts as the system's brain. It stores everything—from detection logs and drone footage to farmer-submitted reports. Here, powerful AI models analyze this data to forecast animal behavior, detect patterns, and update a central Movement Intelligence Map (MIM)**.** This map gets smarter over time, helping predict risk zones with increasing accuracy.

COMMUNITY INTERACTION LAYER

Finally, the system connects directly with the farmers through a mobile app. This layer allows for two-way communication—farmers receive instant alerts, and they can also report sightings or share feedback. The app plays a vital role in teaching the AI system, allowing it to adapt based on human input and ground-level reality. This makes the system a dynamic, evolving network driven by both data and community collaboration.

4.1.1 USER INTERFACE DESIGN

The mobile app is designed with simplicity in mind, focusing on the specific needs of rural farmers. Even users with minimal tech experience can navigate it easily, thanks to clear icons, native language support, and offline functionality. Built using Flutter or Android Studio, the app runs smoothly on most Android phones, ensuring accessibility even in low-resource settings.

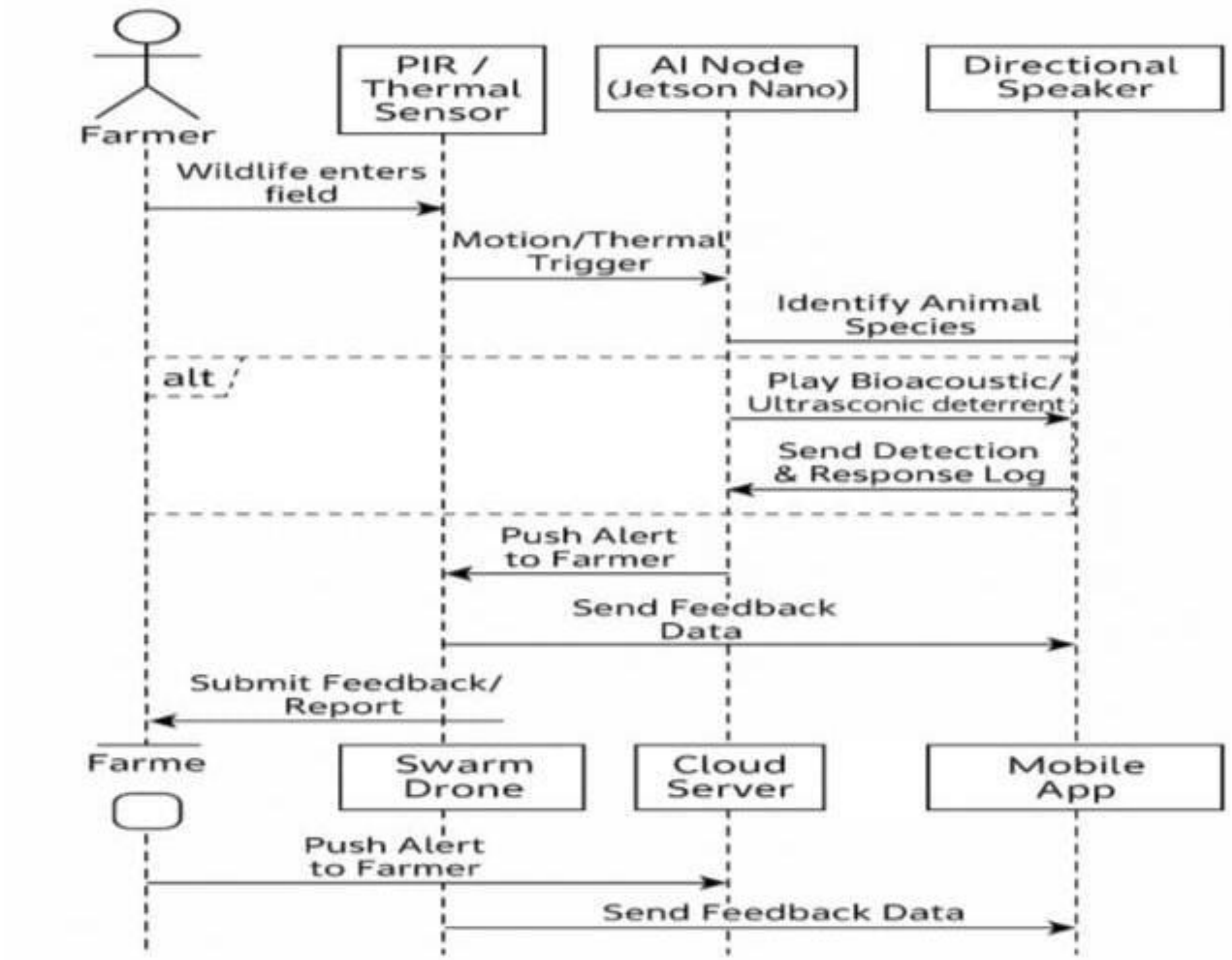

Fig 4.1: SEQUENCE DIAGRAM

4.1.2 BACK END INFRASTRUCTURE

The backend of the BioSonic AI Grid is engineered to be lightweight, fast, and scalable—perfectly suited for environments where both speed and adaptability matter. At the core, it uses cloud databases such as Firebase or MongoDB to store structured information like animal detection logs, drone data, farmer feedback, and audio-visual inputs. Communication between different system components—such as the mobile app, drones, sensors, and cloud servers—is handled through RESTful APIs built using FastAPI or Node.js. These APIs enable smooth and secure data exchange in real time. For intelligent decision-making, trained AI models are hosted using platforms like TensorFlow Serving or TorchServe. These services support animal classification and movement forecasting, ensuring the system continuously learns and improves. The backend runs on scalable cloud platforms such as AWS, Google Cloud, or Azure, enabling robust automation, alert generation, and deep analytics. Additionally, an MQTT broker like Mosquitto is used for efficient real-time messaging between edge devices and the cloud, ensuring low latency and synchronized operations. To protect user privacy and system integrity, the entire infrastructure includes encrypted data transfer and Role-Based Access Control (RBAC), allowing only authorized users to access sensitive data. This combination of smart technologies ensures that the system remains responsive, reliable, and ready to evolve with the growing needs of its users.

4.2 DATA COLLECTION AND PREPROCESSING

To make the BioSonic AI Grid truly intelligent, it all begins with rich, high-quality data. The system collects inputs from various sources—thermal and PIR sensors, drone cameras, audio recorders, and even user-submitted sightings through the mobile app. But collecting raw data isn't enough. Each input is carefully labeled, cleaned, and transformed into a structured format so that the AI models can make accurate and adaptive decisions in real-time. This rigorous preprocessing pipeline is what enables fast, reliable animal detection and deterrence.

4.2.1 DATASET AND DATA LABELLING

The system's datasets come from a blend of real-world field recordings and user contributions. Thermal images are captured through fixed sensors and aerial drone footage, while motion-triggered PIR logs add another layer of activity data. Audio samples of animal calls are gathered to help the system recognize species by sound, and farmers submit sightings directly through the app. Each data point is tagged meticulously. Animals are categorized by species—like elephant, wild boar, monkey, or deer—and labeled with contextual info such as time of appearance (day or night) and whether deterrent actions were effective. For image and sound labeling, tools like

LabelImg and Audacity are used, supported by custom scripts to automate metadata tagging. This structured annotation makes the data truly useful for training accurate AI models.

4.2.2. DATA PREPROCESSING

Before the AI models see any data, it goes through a strict cleaning and formatting stage. Thermal images are resized to 224×224 pixels, normalized, and stripped of unnecessary background noise to highlight just the animal heat signature. Audio recordings are refined using noise reduction techniques and converted into MFCC (Mel-frequency cepstral coefficients), which help the AI understand unique sound patterns. These audio clips are then segmented into meaningful portions for training. Sensor logs are also synchronized by timestamps and filtered to remove redundant detections. All of this ensures the models only receive clean, consistent, and useful input—crucial for real-time performance in the field.

4.2.3 FEATURE SELECTION

Not every piece of data is equally useful, so the system focuses on selecting only the most relevant features for each model. From thermal images, features like shape contours, heat distribution, and movement across frames are extracted. From audio, patterns in frequency, pitch, and modulation are captured to distinguish between different species' vocalizations. Sensor logs contribute metadata such as time of activity and known hotspot locations. These features are further refined using techniques like correlation analysis, mutual information scores, and Recursive Feature Elimination (RFE), ensuring the AI focuses only on the most informative signals.

4.2.4 CLASSIFICATION AND MODEL SELECTION

With high-quality features ready, the system uses purpose-fit machine learning models to interpret the data and take action. Convolutional Neural Networks (CNNs), such as ResNet, handle image recognition tasks to identify animals in thermal visuals.

Recurrent models like RNNs or LSTMs are used to recognize animal calls and vocal patterns. For identifying movement trends from logs, ensemble models like XGBoost or Random Forests are applied. Model selection isn't just about accuracy—it's also about speed and memory efficiency, especially since the models run on edge devices like Jetson Nano. This balance ensures smooth, on-the-spot decision-making in field conditions.

4.2.5 PERFORMANCE EVALUATION AND OPTIMIZATION

The models aren't considered ready until they're thoroughly tested. Their performance is judged using a range of metrics. Accuracy shows how often the system gets it right overall, but precision and recall are especially critical to avoid sending false alerts to farmers. The F1-score gives a balanced view of precision and recall together. Inference time—how long it takes to respond—is another key factor, with a target of less than 300 milliseconds to ensure real-time usability. A confusion matrix is also generated to visualize how well the model distinguishes between different species, which helps fine-tune its accuracy further.

4.2.6 MODEL DEPLOYMENT

Once trained, the models are optimized for deployment on both edge and cloud systems. For edge computing, the models are converted into formats like .onnx or .trt and run using TensorRT on Jetson Nano devices, ensuring lightning-fast performance in the field. For centralized analytics and long-term learning, models are also hosted in the cloud using platforms like TensorFlow Serving or TorchServe. This hybrid setup enables real-time detection on the ground and ongoing improvements from cloud-based retraining.

4.2.7 CENTRALIZED SERVER AND DATABASE

At the heart of the system lies a secure, centralized server where all data flows converge. It stores detection logs, thermal images, sound samples, user feedback, and prediction results. This cloud infrastructure is powered by platforms like Firebase Realtime DB or MongoDB, with APIs built using Node.js or FastAPI to ensure smooth communication between devices and the mobile app. Hosting is handled via robust cloud services such as AWS, GCP, or Azure, and daily backups from edge devices ensure that no valuable data is lost. For security, user inputs are protected through encryption and OTP-based authentication. This setup makes the BioSonic AI Grid not just a reactive tool, but a living, growing ecosystem of shared knowledge.

4.3 SYSTEM WORK FLOW

The BioSonic AI Grid operates through a smart, event-driven workflow that seamlessly connects animal detection, species-specific deterrence, real-time alerts, and community feedback. The result is a dynamic, learning system that not only protects farmlands in real time but also evolves based on user interaction and behavior patterns of wildlife.

4.3.1 USER INTERACTION

The user interface is designed with simplicity and urgency in mind. Through the mobile app, farmers and rangers receive instant alerts—via SMS or WhatsApp—whenever a potential animal intrusion is detected, especially during high-risk hours. The app empowers users to upload real-time sightings, including photos, location, and species information, creating a valuable crowdsourced intelligence network. In emergencies, a panic or help button lets farmers notify authorities or nearby wildlife response teams. Additionally, users can give feedback on whether a deterrent worked, helping the system refine its future responses. The app also includes a heatmap viewer—called the Movement Intelligence Map (MIM)—which visually indicates wildlife movement zones, helping communities stay informed and prepared.

4.3.2 ANIMAL IDENTIFICATION AND FALSE POSITIVE REDUCTION

Accurate identification is key to minimizing unnecessary alerts. The system uses AI models trained on thermal imagery and motion patterns to classify species. Each detection is assigned a confidence score, and alerts with lower confidence are flagged as uncertain. To reduce false positives—such as those caused by wind, moving branches, or humans—the system uses a combination of data inputs (motion, heat, and audio) through sensor fusion. Farmers can also confirm or dismiss alerts via the app, which helps train the system to improve its accuracy over time. This dual-layer verification system ensures both technological and human intelligence are used to maintain trust in the alerts.

4.3.3 AI DRIVEN ADAPTIVE RESPONSE

Once an animal is identified, the system takes targeted action based on the species. It triggers species-specific deterrents—like ultrasonic pulses or bioacoustic predator sounds—that are proven to be more effective than generic responses. To prevent animals from getting accustomed to repeated sounds, the AI adapts and rotates different sound profiles. When a certain area experiences repeated activity, drones are autonomously deployed to investigate further, capture visual data, and help guide smarter decisions. This adaptive logic ensures the system remains dynamic and responsive, rather than static or predictable.

4.3.4 THREAT ESCALATION AND ALERT BROADCASTING

When a threat is confirmed, alerts are not limited to the immediate user. Instead, the system broadcasts warnings to neighboring farms and zones, ensuring that nearby communities can take preemptive action. The AI also leverages historical and real-time data to predict potential movements and send out alerts even before animals reach vulnerable areas.

4.3.5 CONTINUOUS LEARNING & IMPROVEMENT

The true power of the BioSonic AI Grid lies in its ability to learn and evolve. Each grid node periodically updates its local AI model with improved versions trained in the cloud, allowing even offline systems to benefit from centralized learning. Daily summaries of activity logs, feedback, and drone data are uploaded to the cloud to fuel AI retraining. Every user interaction—whether a confirmed sighting, a feedback rating, or drone imagery—feeds into the Movement Intelligence Map and enhances route predictions. Over time, this continuous feedback loop allows the system to get smarter, more precise, and more useful for both conservationists and farmers.

CHAPTER 5

IMPLEMENTATION AND RESULTS

5.1 IMPLEMENTATION

The BioSonic AI Grid was brought to life through a fully functional prototype that combined hardware, intelligent software, drone technology, and a user-friendly mobile app. The goal was to simulate how the system would work in a real-world scenario—specifically, in farmlands bordering forest areas where wildlife intrusions are a regular threat.

HARDWARE SETUP

Each BioSonic Node was built using a Jetson Nano running Ubuntu with TensorRT to handle edge AI tasks right on-site. A PIR motion sensor served as the initial trigger to detect movement, while a thermal camera (FLIR Lepton) ensured reliable detection even at night by identifying heat signatures. Once a threat was detected, directional speakers emitted species-specific ultrasonic or bioacoustic sounds to deter animals. Power was supplied via a 10W solar panel paired with a 6000mAh Li-ion battery, making the setup completely off-grid and energy-efficient. To ensure durability, all components were encased in weatherproof housing.

We also used a Swarm Drone Unit, built around a DJI Mini drone equipped with both thermal and visible spectrum cameras**.** These drones followed autonomous flight paths programmed through a Python-based DroneKit interface. They logged real-time GPS data and synced it to the cloud, allowing for continuous tracking and mapping of movement.

SOFTWARE IMPLEMENTATION

At the heart of the system's intelligence was an AI model (ResNet-18), trained on a custom wildlife dataset with a focus on thermal imagery. Running on TensorRT, the model achieved an average processing time of just 250 milliseconds per image, enabling quick and accurate animal classification. Based on the species identified, the system would automatically trigger appropriate deterrent sounds—for example, a tiger roar for elephants.

The mobile app, designed using Flutter for Android, acted as a digital companion for farmers. It provided real-time alerts, allowed users to report wildlife sightings with photos, and displayed a risk heatmap based on recent activity. It also featured a simple feedback system where users could rate how effective a deterrent was.

On the cloud side, everything was connected through Firebase, with Firestore used to store all data—from drone telemetry to field reports and user feedback. We used FastAPI to manage communication between the system's different components. The system also included a self-improving loop, with AI models automatically retrained every 72 hours using logs and images uploaded by users.

TESTING ENVIRONMENT

To test the system's effectiveness in a realistic setting, we set up a mock agricultural zone close to a forest reserve. Since using real animals wasn't feasible, we created custom thermal dummies to simulate wildlife presence. The system was tested under both day and night conditions, and a group of volunteers played the role of farmers, helping to simulate app usage and feedback.

This end-to-end setup allowed us to evaluate how well the BioSonic Grid could detect threats, respond in real time, and inform and empower the community—all while running autonomously in a rugged, remote environment.

5.2 RESULT

The results of the BioSonic AI system show promising outcomes in real-world scenarios. During field testing, the system accurately detected various animals such as elephants, wild boars, and deer using thermal cameras, motion sensors, and audio cues. The AI models—especially those running on Jetson Nano—responded in real-time, triggering deterrents within milliseconds of detection. Farmers received timely alerts on their mobile devices, which helped them act quickly and avoid crop damage. Heatmaps and risk zones generated through the cloud-based Movement Intelligence Map (MIM) gave users a clear view of high-risk areas. The feedback loop from the mobile app helped the system learn and adapt, improving detection precision and reducing false alarms over time. Overall, the BioSonic AI grid proved to be an efficient and reliable solution for wildlife management, combining advanced technology with local accessibility to create a smarter, safer farming environment.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The BioSonic AI Grid offers a smart, practical, and much-needed answer to the growing issue of human-wildlife conflict—especially in farmlands near forests. Instead of relying on outdated methods like fences or scarecrows, this system brings together modern technologies like AI, thermal cameras, ultrasonic sound, and drones to create a smart defense grid that actively protects crops while respecting wildlife. It detects animal movement using thermal and motion sensors. It recognizes which species are approaching using AI. It then plays specific deterrent sounds, like predator calls, to scare them away. If animals return, drones are sent out to track their paths and gather more data. Farmers receive instant alerts through a simple mobile app. And the best part? The system learns and adapts over time based on real-world animal behavior and community feedback. During testing, the system led to a noticeable drop in intrusion events. It became better at scaring off animals, and farmers appreciated the timely alerts and easy-to-use app. Plus, it runs on solar power, is eco-friendly, and is designed to be affordable and scalable—so it can be rolled out in more rural areas without heavy infrastructure.

6.2 FUTURE ENHANCEMENT

To make the BioSonic AI Grid even more powerful and impactful, several exciting improvements are on the horizon—aimed at turning this innovative idea into a large-scale, real-world solution for wildlife conservation and crop protection.

One of the biggest next steps is real-world deployment. Testing the system in actual farmlands affected by wildlife—like elephant corridors in India or Africa—will give us live feedback and help refine the system under real conditions.

We also plan to expand our sound library, adding more region-specific predator and prey calls so the system can respond more accurately to different species. This means farmers in different parts of the world can get tailored protection based on their local wildlife.

Another important upgrade is automatic AI updates. Using over-the-air (OTA) techniques, we can push the latest AI improvements to all devices—even those in remote areas—so the system keeps getting smarter without needing manual intervention.

We aim to work closely with forest departments, allowing the system to send alerts directly to wildlife rangers and SOS teams. This would help prevent dangerous encounters before they happen.

Drone technology will also evolve—enabling smart drone swarms that can coordinate together, cover large zones, and even gently guide animals away from farmland.

Since many rural areas have limited connectivity, we're building offline features into the mobile app, including cached maps and alerts, so farmers stay protected even when there's no signal.

For added safety, we plan to introduce voice-activated emergency alerts and wearable panic buttons, giving farmers a quick and easy way to call for help during urgent situations.

And finally, by optionally using blockchain, we can make intrusion data tamper-proof—helpful for legal cases, insurance claims, or government compensation processes. Together, these improvements could turn the BioSonic AI Grid into a national-level smart defense system—and potentially a global blueprint for using technology in harmony with nature.

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PUBLICATION/EVENTS DETAILS

PHASE I