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Intelligent UAV Surveillance and AI Analytics Framework for DISCOM Operations

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ABSTRACT
Electricity Distribution Companies (DISCOMs) manage extensive and widely distributed power networks, where traditional manual inspections are often slow, labor-intensive, and no longer sufficient for today's expectations of reliability and efficiency. This work introduces a holistic approach for implementing drone (UAV) technologies combined with Artificial Intelligence (AI) to advance operations, safety, and business performance in power distribution. Employing drones equipped with various sensors such as RGB, thermal, zoom, and LiDAR, it examines essential applications like equipment health checks, monitoring of vegetation and right-of-way, outage assessments, theft prevention, and consumer mapping. An integrated technical solution is outlined, covering the entire process from drone-based data collection and on-the-spot processing to cloud storage, AI-powered fault detection and prioritization, and automated work order creation that connects with DISCOMs' existing enterprise platforms (GIS, OMS, ERP, MDM). The paper also outlines practical strategies for gradual deployment in Indian utilities, focusing on tangible metrics including reduced outage durations (SAIDI/SAIFI), decreased AT&C losses, and improved crew safety. The findings show that combining drones with AI not only improves inspection efficiency but also transforms them into key tools for predictive maintenance, revenue assurance, and informed decision-making within power distribution.

KEYWORDS: Drones, UAV, Artificial Intelligence, DISCOM, LiDAR, Revenue, Cloud Computing.

1. Introduction

Power distribution networks represent the last and often the most intricate stage in the delivery of electricity. In India, distribution companies (DISCOMs) oversee a vast array of assets, including 11 kV feeders, low-tension lines, distribution transformers, switches, and consumer connections, which are distributed throughout both crowded cities and far-flung rural areas. These organizations consistently face issues such as significant technical and commercial losses, safety hazards, unreliable asset documentation,

and slow identification of faults.
Recent progress in drone technology, compact sensors, and artificial intelligence has opened new possibilities for inspecting electrical distribution networks. Drones allow faster, non-intrusive, and information-rich assessments of field assets. This paper brings together the operational, technical, and analytical aspects of using drones in DISCOM environments and presents a practical, end-to-end implementation approach suited to Indian regulatory conditions and utility operations.

2. Institutional Context and Precedents

The use of drones in Indian power utilities is no longer limited to trials and pilot projects. Transmission utilities such as MPPTCL have already released tenders for drone-based inspection of EHV and HV corridors, demonstrating that regulatory, procurement, and DGCA compliance processes are well established. At the distribution level, utilities like BSES Rajdhani Power Ltd (Delhi) and Assam Power Distribution Company Ltd (APDCL) have issued RFPs for AI-supported drone inspections across 11 kV networks.
These developments clearly indicate that:

- Drone operations are now formally recognized within Indian power utilities
- DGCA DigitalSky procedures for such operations are well understood and workable
- Utilities are steadily moving from manual patrolling toward data-driven asset management practices

3. Drone Sensing Modalities for Distribution Networks

Modern distribution networks benefit from using a mix of complementary drone sensors to deliver thorough, safe, and repeatable asset assessments. Each sensing method helps detect a different category of defects and risks, and together they create a layered view of network condition that manual inspections cannot match.

3.1 RGB Visual Imaging

High-resolution RGB cameras, usually between 20 and 48 megapixels, are central to visual inspections of distribution assets. They allow close examination of poles, cross-arms, insulators, jumpers, clamps, switches, and LT joints. Subtle signs such as cracks, corrosion, loose or missing fittings, oil leaks, and other physical damage can be clearly documented through geo-tagged images. These photographs support routine maintenance as well as regulatory record-keeping by creating a reliable visual history of asset condition over time.

3.2 Thermal / Infrared Imaging

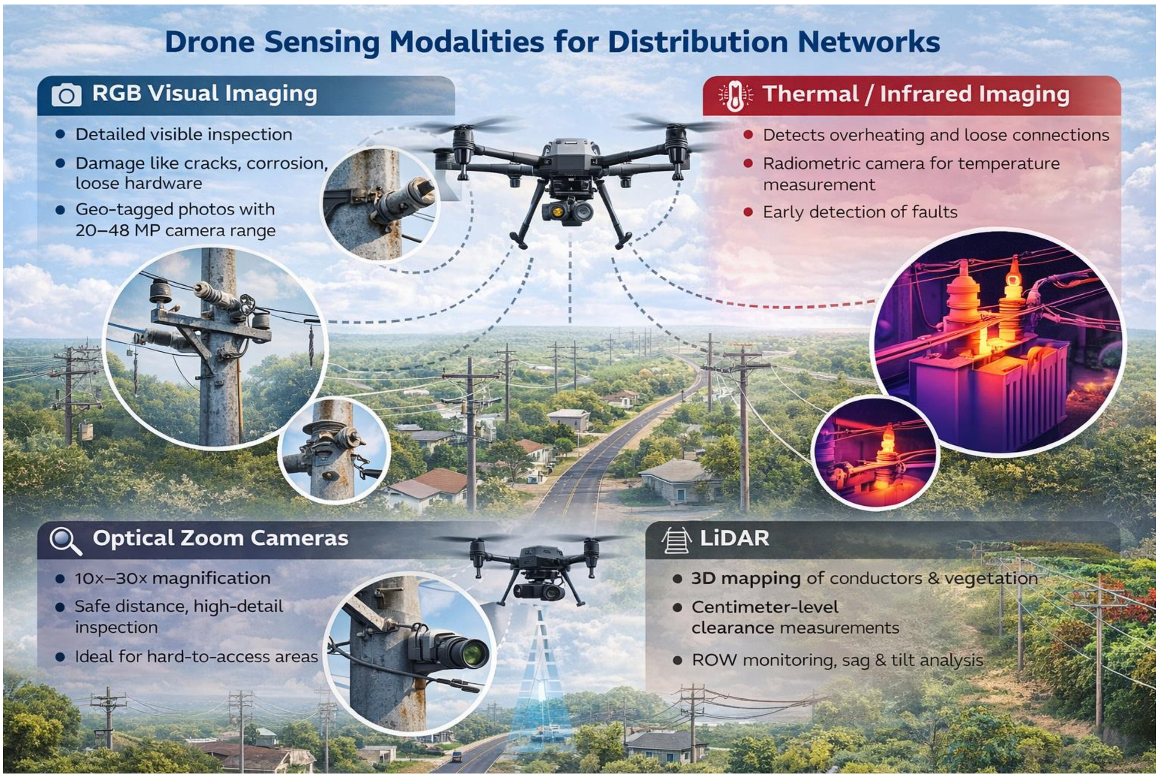
Radiometric thermal cameras provide an essential diagnostic capability by capturing heat patterns that cannot be seen in normal visual inspections. They help identify unusual temperature rises in DT bushings, jumpers, overloaded phases, AB switches, fuse contacts, and LT joints. Differences in temperature (ΔT) serve as early signs of loose connections, overloading, phase imbalance, or developing component faults. Detecting these issues in advance allows utilities to move toward condition-based and predictive maintenance rather than reacting after failures occur.

3.3 Optical Zoom Cameras

Optical zoom cameras offering 10× to 30× magnification make it possible to examine assets in fine detail from a safe distance. This is particularly valuable when equipment is live or positioned in crowded, elevated, or difficult-to-reach locations. With this capability, operators can closely inspect insulators, connectors, and fittings without breaching safety clearances, reducing risk to personnel while preserving inspection quality and uninterrupted operations.

3.4 LiDAR

LiDAR sensors deliver highly accurate, centimeter-level 3D mapping of conductors, nearby vegetation, structures, and terrain. This capability is especially useful for Right-of-Way monitoring, assessing conductor sag, detecting pole tilt, and checking clearance violations along distribution corridors. The detailed spatial models produced by LiDAR help utilities with regulatory compliance, vegetation planning, and network resilience analysis—particularly across large and varied service areas.



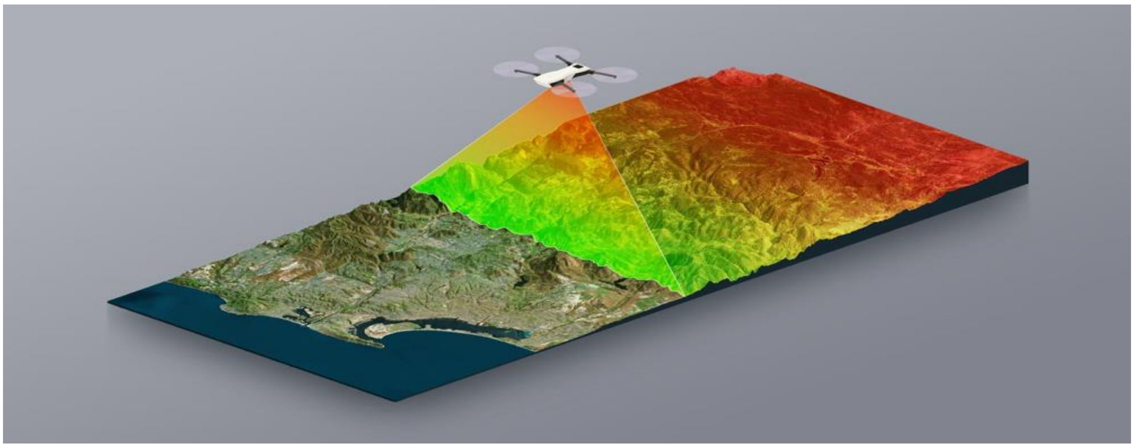


Fig 3.4.1

Fig 3.4.2

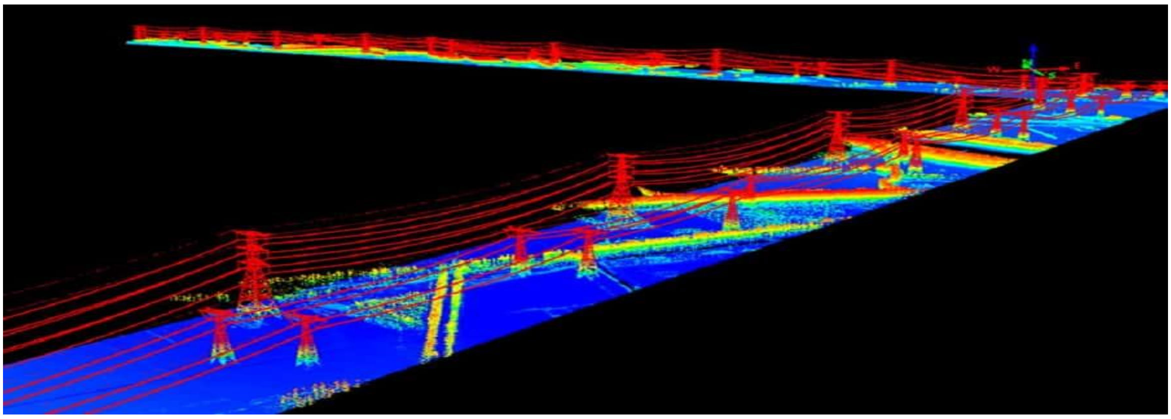


Fig 3.4.3

4. Core Operational Use Cases

Combining drones with AI, cloud platforms, and GIS opens up a range of practical, high-value applications across the distribution network. These applications help improve reliability, safety, revenue assurance, and data accuracy for DISCOMs, while greatly reducing the need for manual field inspections.

4.1 Network Asset Inspection

Drones are regularly used to inspect 11 kV feeders, LT lines, distribution transformers (DTs), capacitor banks, RMUs, reclosers, and related equipment. The findings are translated into simple condition grades (such as A/B/C/D) to create a consistent health score for each asset. Identified issues are geo-tagged and linked to specific components, allowing inspection results to flow directly into maintenance planning and automated defect-to-work-order processes within existing enterprise systems.

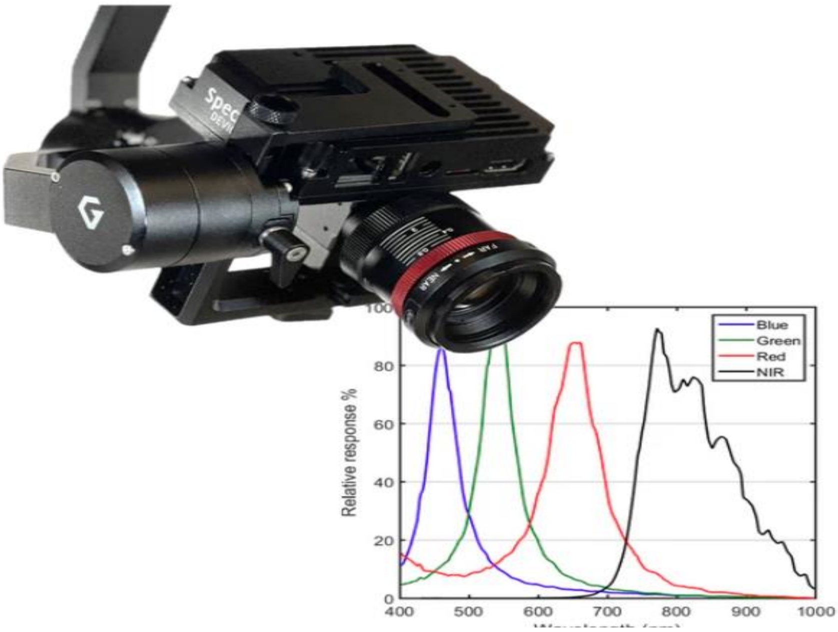


Fig 4.1.1

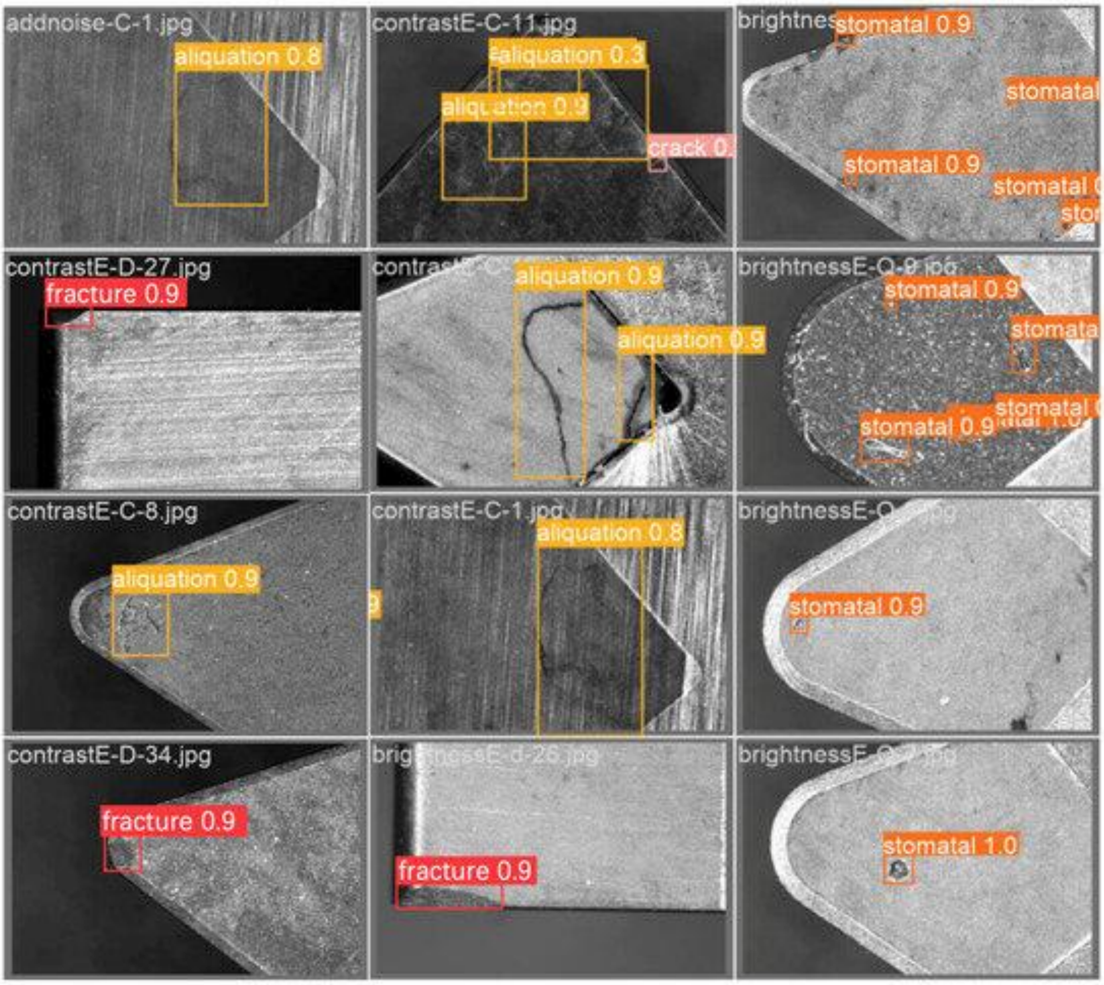


Fig 4.1.2

4.2 Vegetation and Right-of-Way (ROW) Monitoring

Vegetation encroachment is a major source of distribution faults, especially during monsoon storms and peak summer conditions. Drone corridor patrols using LiDAR or high-resolution photogrammetry can accurately measure the clearance between conductors and nearby trees along feeder routes. These insights help utilities prioritize trimming and vegetation control based on actual risk, shifting from reactive cutting to planned, data-driven schedules that improve both reliability and safety.

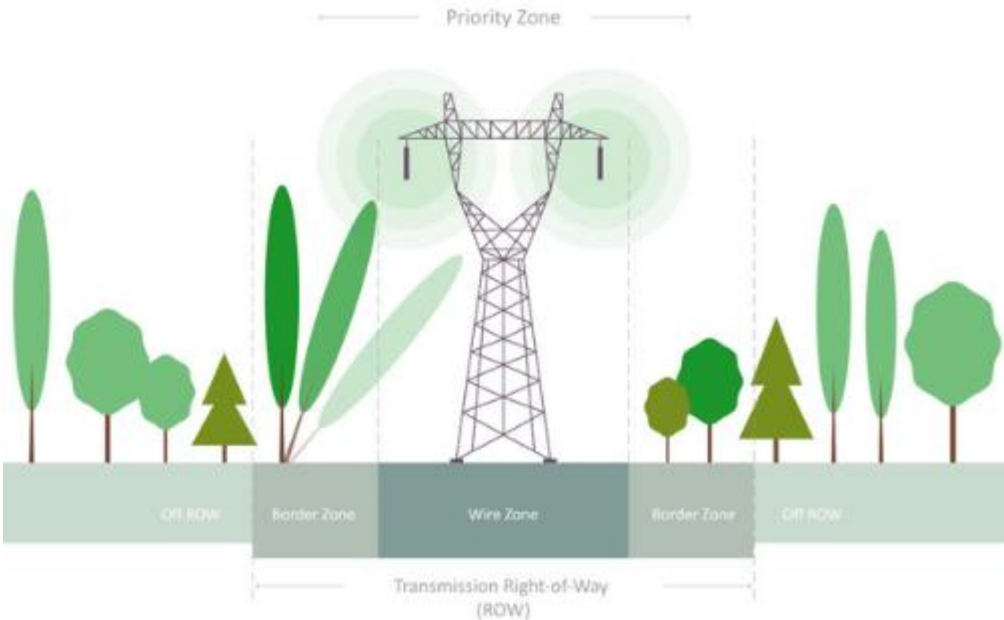


Fig 4.2

4.3 Outage Patrol and Restoration Support

During fault conditions, drones can patrol 20–60 km of feeder lines far faster than ground teams. They help quickly spot snapped conductors, damaged insulators, burnt jumpers, fallen trees, pole damage, and even theft-related cuts. Live video and images sent to the control room shorten the time needed to locate faults, speed up restoration, and support improvements in reliability metrics such as SAIDI and SAIFI.

4.4 Anti-Theft and Unauthorized Load Detection

Drone surveys can capture clear visual proof of power theft and unsafe practices, such as illegal hooking, bypassed service lines, unauthorized tapping from DTs, and risky encroachments near live conductors. When these observations are combined with billing data and MDM/AMI analytics, utilities can pinpoint likely theft pockets, plan focused enforcement actions, and reduce AT&C losses more effectively.

4.5 Consumer Indexing and GPS Tagging

Using RTK/PPK-enabled GNSS along with orthomosaic mapping, drones can accurately link each consumer to the corresponding DT and feeder. This creates a unified and reliable "network truth" layer that aligns field assets and consumers with GIS, billing, ERP, and MDM platforms. Better indexing supports more accurate load studies, outage impact analysis, planning, and data consistency across systems.

Operationally, the main constraint is no longer data capture—drones handle that efficiently—but what happens afterward. The real effort lies in filtering what matters, validating accuracy, turning imagery into actionable tasks, and deciding priorities. This is where AI/ML, cloud-scale processing, and tight GIS integration become essential for managing drone data effectively at scale.

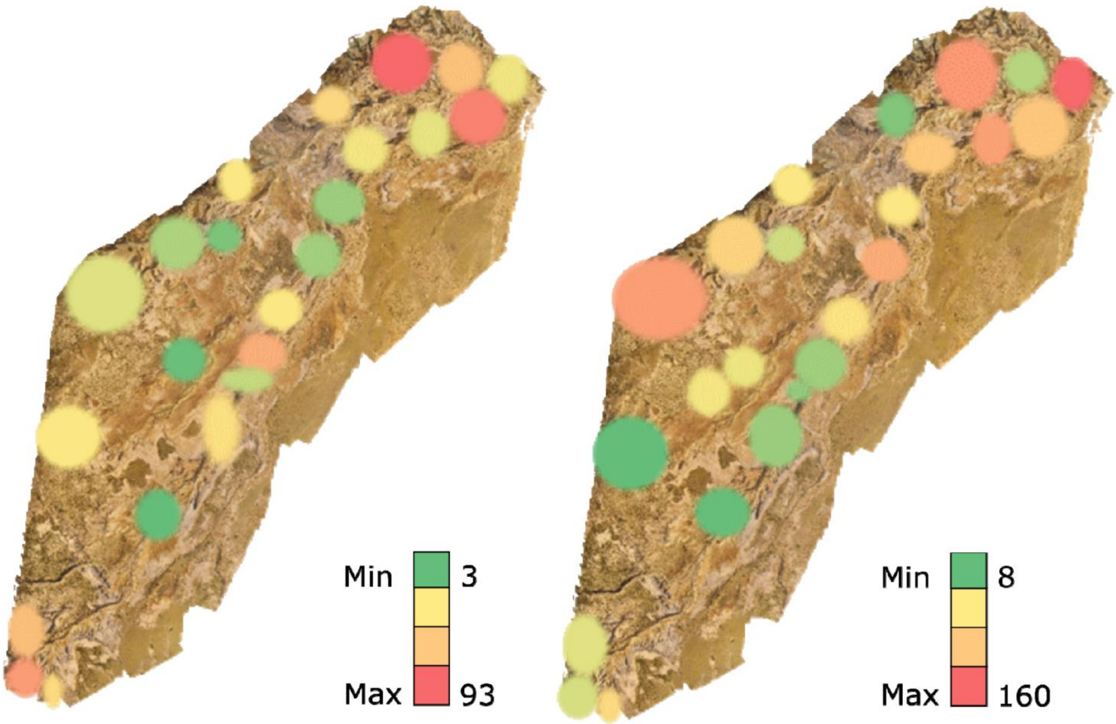


Fig 4.5

5. The Colossal Data Challenge

Large UAV surveys along distribution corridors generate massive volumes of high-resolution, multi-sensor data—RGB images, thermal frames, LiDAR point clouds, videos, and detailed GNSS/geospatial metadata. As operations expand from individual feeders to entire divisions and regions, the data grows at a pace that quickly overwhelms manual review and traditional storage approaches.

Without automated analytics and structured data pipelines, valuable information risks being stored but never truly used—archived rather than acted upon. The core issue is no longer data collection; it is turning raw data into clear, prioritized field actions quickly.

The real bottlenecks include:

- Distinguishing meaningful defects from background visual noise
- Ensuring positional and radiometric accuracy
- Extracting practical insights such as hotspots, encroachments, theft indicators, and clearance risks
- Delivering outputs in formats that connect directly with GIS, OMS, EAM, and field workflows

Addressing this requires intelligent automation, scalable cloud-based geospatial systems, and close integration between AI analytics, GIS platforms, and DISCOM operations—so that large data volumes translate into better, faster decisions rather than operational burden.

What “colossal” looks like in practice:

Typical data yield from a 10 km 11 kV feeder survey.

Data Type	Typical Specs	Approx Size
RGB photos (20–48 MP, 80% overlap, ~6,000 images)	Orthomosaic input	**35–60 GB**

Data Type	Typical Specs	Approx Size
Thermal radiometric set (R-JPEG/TIFF)	Hotspot analytics	**8–15 GB**
LiDAR point cloud (LAS/LAZ)	3D corridor model	**20–35 GB**
Orthomosaic GeoTIFF (2–3 cm GSD)	GIS base layer	**8–12 GB**
DSM/DTM elevation models	Clearance/ROW	**5–8 GB**
4K inspection video	Visual audit trail	**10–20 GB**
RTK/PPK + metadata	GNSS logs, EXIF	**0.3–0.8 GB**
GIS vectors (tagged assets)	Poles, DTs, consumers	**0.2–0.5 GB**

Table 5.1

Coverage Block	Data Volume
Feeder corridor UAV mapping	**75–100 TB**
DT & habitation detail mapping	**20–30 TB**
Thermal campaigns (seasonal)	**10–15 TB**
LiDAR corridor models	**25–40 TB**
Processed GIS/AI layers	**8–12 TB**

Table 5.2

6. End-to-End Technical Architecture

6.1 Layer A — Acquisition (Drone + Sensor Stack)

Layer A represents the field data capture tier, where RTK/PPK-enabled drones gather rich, multi-sensor observations of the distribution network in a single flight. This approach reduces time in the field while providing broad diagnostic coverage.

The sensor suite is designed to capture both visible and hidden indicators of asset health:

- 20–48 MP RGB cameras record clear visual evidence of structural issues such as corrosion, cracked insulators, loose fittings, and cross-arm damage, supporting condition assessment and compliance documentation.
- 10×–30× optical zoom allows close inspection of live components—jumpers, connectors, and insulators—from a safe distance without breaching electrical clearances.
- Radiometric thermal sensors reveal heat patterns linked to hotspots, overloading, phase imbalance, DT bushing stress, and early-stage faults, aiding predictive maintenance and loss analysis.
- LiDAR (where used) produces accurate 3D corridor models for sag measurement, clearance checks, vegetation intrusion, pole tilt detection, and terrain mapping.

With RTK/PPK GNSS, positional accuracy improves from meters to centimeters, enabling reliable pole–DT–feeder mapping, consistent before-and-after comparisons, and GIS-ready clearance analysis.

Outcome: Drone data moves beyond simple imagery to become a precise, geospatially aligned, decision-ready digital view of the DISCOM network.

6.2 Layer B — Edge Compute (On-Site / Vehicle / Division Office)

Layer B is the edge-compute tier, located close to field operations—at the inspection site, inside a mobile unit, or at the division office. Its role is to cut delays, improve data quality, and support quick decisions before information is sent to central or cloud systems.

The first task at the edge is immediate data validation. Automated checks identify issues like motion blur, poor exposure, focus problems, or gaps in spatial coverage. Spotting these on the spot allows the team to re-capture data while still in the field, avoiding repeat visits and missing information.

Edge processing also supports quick operational triage. Clear thermal hotspots, major hardware damage, risky vegetation growth, or clearance violations can be flagged within minutes of landing the drone. This enables field teams and control rooms to take prompt safety or maintenance actions even before detailed central analysis begins.

Because drone surveys produce large volumes of imagery, thermal data, and LiDAR point clouds, the edge layer performs smart compression and secure encryption before transmission. This reduces bandwidth needs and supports cybersecurity requirements important for critical infrastructure.

Another advantage is the ability to function in areas with poor or no connectivity. For remote feeders and substations, edge systems allow continuous processing, secure local storage, and later synchronization once a network becomes available.

Typical setups include rugged laptops or mobile workstations with GPU capability, compact industrial GPU devices, and local high-speed storage or NAS units. Together, these ensure smooth data handling and transfer to higher-level analytics platforms without interrupting field work.

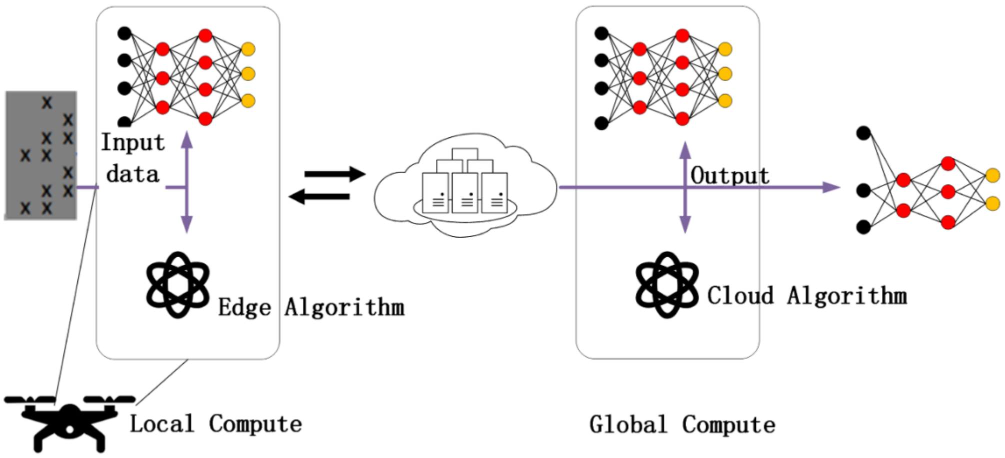


Fig 6.2

6.3 Layer C — Centralized Cloud and Data-Lake

Layer C forms the centralized cloud and data-lake foundation of the framework, built to manage the fast-growing data volumes generated by repeated drone surveys across divisions, circles, and regions. As high-resolution RGB images, thermal data, and LiDAR point clouds accumulate over time, a scalable and reliable cloud setup becomes necessary to maintain performance, control costs, and ensure long-term availability of information.

A tiered storage approach helps balance speed and cost. Hot storage keeps data from recent missions (about 30–90 days) readily accessible for active analysis and operational decisions. Warm storage holds data from earlier seasonal surveys—such as monsoon or summer inspections—useful for comparisons and trend studies. Cold archival storage preserves older data needed for compliance, audits, investigations, or legal purposes, where durability matters more than quick retrieval.

The cloud platform itself should remain provider-neutral to avoid dependency on any single vendor and to support hybrid or multi-cloud setups. Key components include large-scale object storage for imagery, video, thermal datasets, and LiDAR files, along with a well-structured metadata catalog that allows fast searching by asset, location, date, or defect type.

Both streaming and batch processing services are needed to handle near-real-time uploads from edge systems as well as deeper historical analysis. Dedicated machine-learning infrastructure supports model training and deployment for automated defect detection, risk assessment, and predictive maintenance use cases.

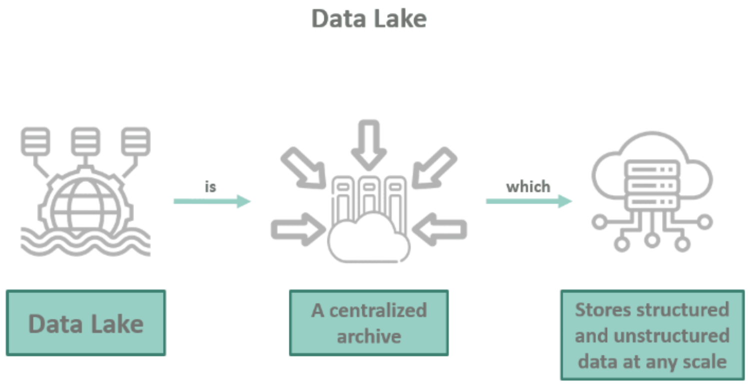


Fig 6.3

6.4 Layer D — AI/ML engine (the "data-to-decision" layer)

This layer converts raw inspection inputs—images, thermal scans, and LiDAR point clouds—into structured insights that operations and maintenance teams can act on directly. It serves as the bridge between data capture and practical field decisions.

Using automated analytics and AI/ML models, the system reviews the collected data to detect and categorize issues such as mechanical damage, corrosion, overheating, and vegetation intrusion. Each issue is assigned a severity score based on measurable factors like temperature rise, extent of damage, clearance gaps, or likelihood of failure.

Every finding is geo-tagged and mapped to specific assets—poles, conductors, insulators, or transformers—using precise spatial references. This allows traceability over time and smooth integration with GIS and asset management platforms.

From this analysis, the system can suggest appropriate maintenance actions, such as inspection, tightening, part replacement, load adjustment, or urgent shutdown, reducing the need for manual interpretation and speeding up response. A broader risk ranking is then created by combining defect severity with asset importance, load criticality, and environmental context, helping utilities prioritize work across feeders, divisions, and regions for maximum operational and safety benefit.

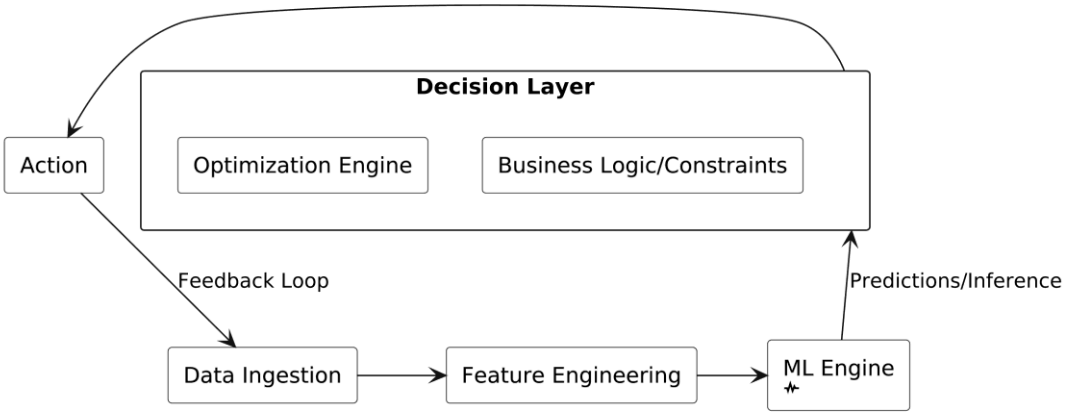


Fig 6.4

6.5 Layer E — Integration with DISCOM enterprise stack

Layer E focuses on ensuring that insights from the drone–AI system are not isolated, but fully integrated into the DISCOM's existing enterprise platforms. Analytics deliver real value only when their outputs feed directly into the tools already used by engineers, field teams, and management.

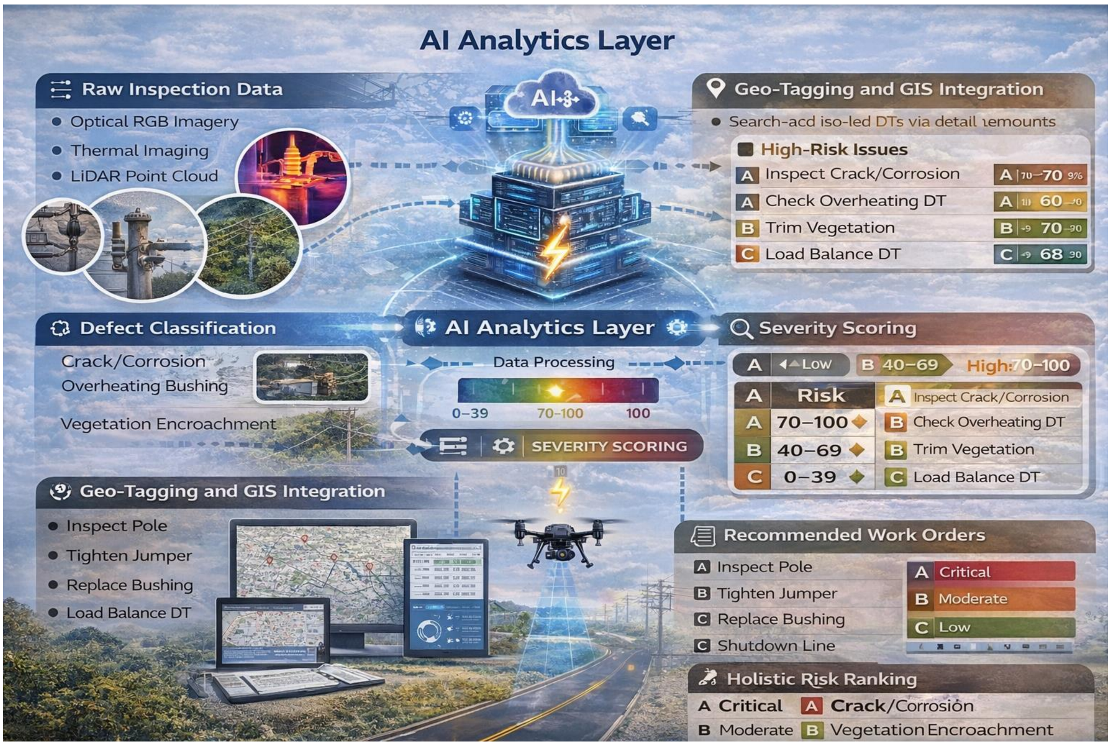
The integration begins with the GIS platform, where inspection results, asset conditions, and detected issues are tied to the official asset records. Linking findings to specific feeders, poles, conductors, and DTs enables clear spatial visualization, trend tracking, and an accurate view of the network across regions and divisions.

When connected to the Outage Management System (OMS), inspection insights can be compared with past fault and outage data. This allows utilities to anticipate failures and shift from reactive repairs to preventive action. High-risk findings can also trigger alerts or early maintenance steps within OMS workflows.

Maintenance and Enterprise Asset Management (EAM) systems receive structured work orders based on the analysis. This supports automatic task creation, crew scheduling, and progress tracking, reducing manual effort and speeding up field response.

Integration with MDM/AMI platforms brings additional value by linking visual and thermal findings with consumption patterns, load irregularities, or suspected theft. This combined view strengthens enforcement measures and improves revenue protection.

Finally, ERP integration ensures that all corrective actions reflect in inventory planning, material management, and cost tracking. This completes the loop between inspection, execution, and financial planning, enabling better budgeting, ROI assessment, and informed decision-making at the enterprise level.



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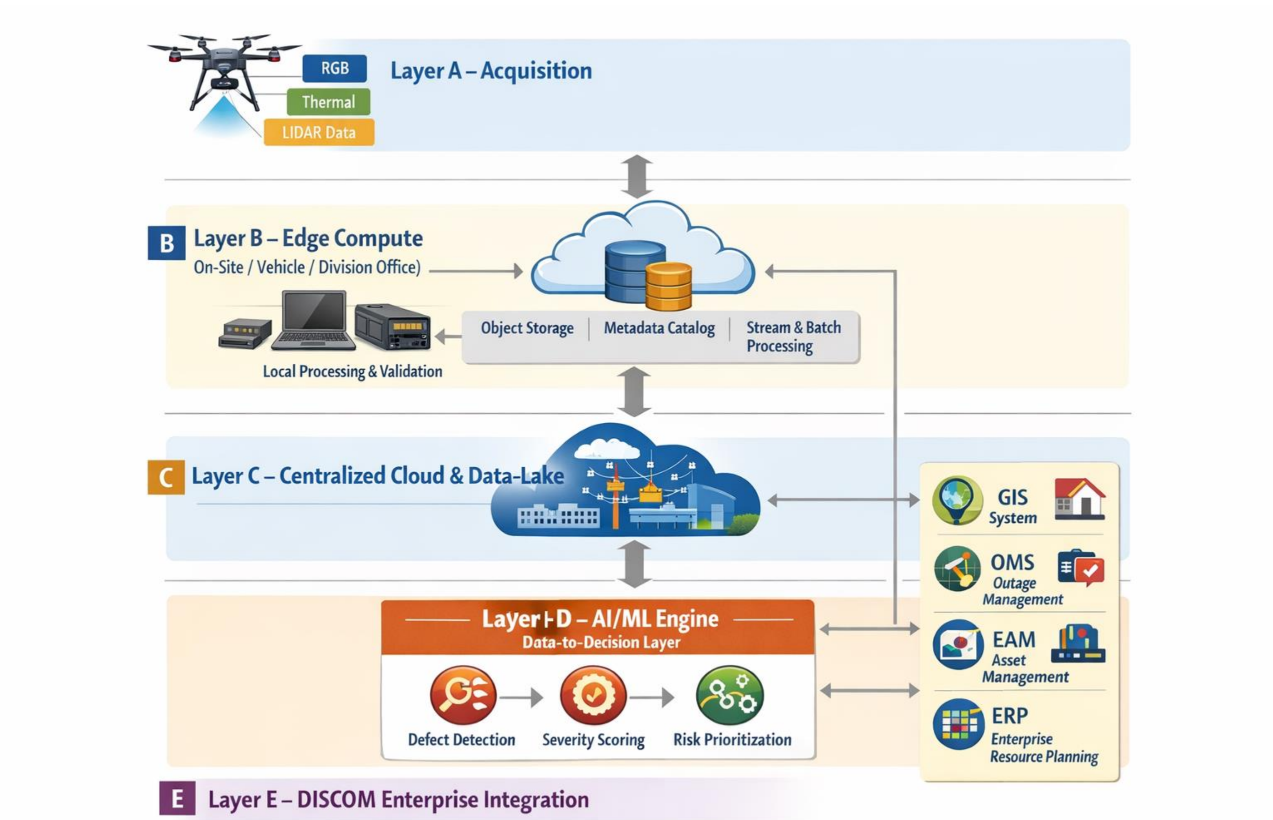

Fig 6.5.2 End- to-End Architecture diagram

7. AI Models and Analytics

This layer serves as the intelligence engine of the framework, turning raw drone data into insights that teams can trust and act upon. Because the data is varied and the use cases are wide-ranging, no single model or method is enough. What's needed is a well-designed, multi-stage analytics pipeline that covers data extraction, quality checks, and clear interpretation for operational use.

7.1 Data Mining: Pulling Meaningful Signals from Raw Drone Data

The first step is to separate useful information from the large volumes of images and sensor outputs collected during drone surveys. Good data mining ensures that AI models further down the pipeline work only with relevant, high-quality inputs.

7.1.1 Metadata-First Mining for Early Operational Gains

Even before applying advanced AI models, meaningful insights can be gained through smart use of mission metadata. Drone data is first organized by feeder, DT/DTR, pole ID, and individual span segments. Additional filters—such as flight altitude, camera angle, and time of capture—help maintain consistency and relevance. Similar or duplicate frames are automatically removed to cut processing effort, and coverage checks highlight any missed poles, spans, or feeder sections.

This stage produces practical outputs like a mission coverage summary, a data completeness score, and an asset-mapping confidence level, giving teams an immediate sense of inspection quality and readiness for deeper analysis.

7.1.2 Content-Based Mining through AI-Led Indexing

AI analysis is then used to automatically label images and video clips with meaningful tags such as "insulator visible," "conductor joint present," "DT identified," "service line detected," "vegetation close to conductor," "construction beneath the line," or "dense LT hooking patterns."

This creates a searchable visual index, enabling operators to run practical queries like: "Show all suspected LT bypass connections on feeder X" or "List spans where vegetation clearance is below the safe limit."

7.2 Data Validation: Building Confidence in the Dataset

Validation is essential because poor or inaccurate inputs can lead to wrong work orders, wasted effort, and added operational risk.

7.2.1 Quality Validation through Computer Vision Checks

Automated quality checks review images for blur or motion blur, exposure issues, low-light noise, lens flare, atmospheric haze, and proper thermal calibration. Positional accuracy is also verified by checking the quality of RTK/PPK fixes (fixed versus float), ensuring the spatial precision needed for utility-grade mapping.

7.2.2 Geospatial Validation

Every image and video frame is checked to ensure alignment between its GPS position, camera orientation, and sensor metadata. The observations are then matched to the nearest known asset—such as a pole or DT—within the GIS records. If inconsistencies appear, for example when the camera angle indicates one location but the GPS shows a noticeable offset, the system automatically flags them for further review.

7.2.3 Label Validation for Training Data

To keep AI training reliable, labels are verified through agreement among multiple annotators. Active-learning loops let the model surface uncertain cases for human review, and drift checks account for new hardware, insulator designs, or construction patterns that appear in the network over time.

7.3 Data Interpretation: Algorithms and Model Families

Because inspection needs vary widely, different types of models are used side by side, each tuned to a particular sensor input and operational purpose.

A) Visual Inspection (RGB and Optical Zoom)

Inputs: RGB/zoom images + GIS asset registry

Outputs: {asset_id, component_type, defect_type, severity_score, evidence_crop, OCR_id, GIS_match_id}

High-level flow:

Preprocess

- Check blur and effective scale (GSD/zoom).
- Apply super-resolution only on blurred regions (if needed).

Detect components

- Use a scale-aware detector (e.g., YOLO + FPN / Deformable DETR).
- Identify poles, insulators, clamps, jumpers, DTs, arresters, cut-outs.

Segment defects

- Run segmentation on detected regions (Mask R-CNN / SegFormer / U-Net).
- Isolate cracks, corrosion, chips, burn marks.

Classify condition

- Component-specific model (e.g., EfficientNet/ConvNeXt) labels health state and defect type.

OCR + GIS match

- Read pole/DT IDs (CRNN/TrOCR).
- Match to GIS using text similarity + location proximity.

Decision output

- Assign severity score and priority ranking per feeder/DT.

Use variance of Laplacian (common, robust):

$$B = \mathrm{Var}\left(\nabla^2 I\right)$$

Convert to a quality weight (0–1), with τ_B as a blur threshold:

$$w_{blur} = \sigma\left(\alpha(B - \tau_B)\right)$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$.

B) Thermal (Radiometric) Interpretation

Thermal ΔT Modeling with RGB Fusion — Hotspot Intelligence

Goal: turn radiometric thermal data into actionable outputs:

{asset, hotspot_location, ΔT, severity, probable_cause, trend_slope}

Workflow:

- **Calibrate & align**

1. Correct for emissivity, reflections, distance, atmosphere.
2. Align thermal with RGB to pinpoint hardware accurately.

- **Locate components**

1. Use RGB detection to identify joints, connectors, bushings, jumpers, fuse points.
2. Map these regions onto the thermal image.

- **Model expected temperature**

Estimate baseline using ambient conditions, load effect, and time of day.

- **Detect anomalies**

1. Compute ΔT for each component region.
2. Flag hotspots using robust statistical checks.

- **Check phase imbalance**

Compare temperatures across phases to derive imbalance index.

- **Track trends**

Compare readings across inspections to measure deterioration rate.

- **Classify likely cause**

Use ΔT pattern, context, and imbalance to infer: loose joint, overload, corrosion, contact resistance, bushing stress, or unknown.

For component i at time t:

$$T_{i,t}^{exp} = T_t^{amb} + \alpha_i I_t^2 + \beta_i TOD_t + \gamma_i$$

- T_t^{amb}: ambient temperature
- I_t: feeder/DT load current proxy (from SCADA/MDM or nearest estimate)
- TOD_t: time-of-day term (captures solar heating / daily bias; can be sin/cos)
- $\alpha_i, \beta_i, \gamma_i$: component-specific coefficients (learned from historical "healthy" data)

C) Vegetation and Right-of-Way (ROW) Monitoring

ROW Vegetation Risk Pipeline — From Mapping to Risk Score

Inputs: RGB orthomosaic ± LiDAR, feeder centerline, poles/spans, past surveys

Outputs: Vegetation zones, clearance gaps, sag data, ROW risk score per span

Workflow:

- **Align surveys over time**

Co-register seasonal orthomosaics (and LiDAR) using RTK/PPK/GCP and point-cloud alignment.

- **Segment vegetation (RGB)**

Use semantic segmentation (e.g., U-Net/SegFormer/DeepLab) to classify vegetation, corridor, ground, structures.

- **Detect vegetation growth**

Compare time-series masks to track canopy expansion along spans.

- **Classify LiDAR points (if available)**

Label ground, vegetation, conductor, poles using filters + ML/point models.

- **Compute clearances**

Measure minimum 3D distance between conductors and vegetation within ROW buffer.

- **Estimate sag (catenary fit)**

Fit curve to conductor points to find lowest sag and clearance profile.

- **Score ROW risk**

Combine clearance, growth rate, and sag margin to prioritize trimming actions.

Let $M_t(x, y) \in \{0, 1\}$ be vegetation mask at time t.
Vegetation area in corridor C:

$$A_t = \sum_{(x,y)\in C} M_t(x, y) \cdot a_{px}$$

where a_{px} is ground area per pixel (m^2/pixel).

Change between two surveys:

$$\Delta A = A_{t_2} - A_{t_1} \qquad g_A = \frac{\Delta A}{t_2 - t_1}$$

(g_A = growth rate, m^2/day or m^2/month)

Catenary model for conductor in span coordinate $x \in [0, S]$:

$$y(x) = a \cosh\left(\frac{x - x_0}{a}\right) + c$$

Fit parameters (a, x_0, c) by minimizing error to LiDAR conductor points (x_i, y_i):

$$\min_{a,x_0,c} \sum_i \left(y_i - \left[a \cosh\left(\frac{x_i - x_0}{a}\right) + c\right]\right)^2$$

Sag (drop from support height y_{end} to lowest point):

$$\text{Sag} = y_{end} - \min_{x\in[0,S]} y(x)$$

D) Theft, Illegal Hooking, and Unauthorized Extensions

Graph-Assisted Visual–Energy Theft Detection (VET-GNN)

A pipeline combining UAV imagery, GIS topology, and meter data to detect theft with low false positives.

Inputs: RGB/zoom images, GIS network map, feeder/DT energy data, AMI/MDM records

Outputs: Ranked theft cases with location, evidence, feeder/DT link, theft type

Workflow:

- **Visual extraction (UAV)**
- Detect wires, poles, meters, junctions, DT bus, cut-outs, illegal taps.
- Build wire centerlines to infer actual connections.
- **Candidate event generation**
- Flag patterns like direct tapping, meter bypass, unauthorized extensions, or DT take-offs.
- Treat each as a possible graph edge.
- **Graph inference (Vision + GIS)**
- Create a graph of poles, DTs, meters, loads.
- Combine GIS links with vision-derived wires.

- Use GNN/probabilistic logic to assess connection legitimacy.
- **Energy anomaly screening**
- Compare feeder input vs billed energy vs expected losses.
- Identify spans with persistent localized mismatches.
- **Score fusion**
- Merge visual evidence, graph plausibility, and energy anomaly into a theft confidence score.

For a feeder f in interval t:

$$R_{f,t} = E_{f,t}^{in} - \sum_{m \in \mathcal{M}_f} E_{m,t}^{meter} - \hat{L}_{f,t}$$

- $E_{f,t}^{in}$: feeder input energy
- $E_{m,t}^{meter}$: metered/billed energy sum under feeder
- $\hat{L}_{f,t}$: expected technical loss (from model or benchmark)

Normalize to an anomaly score:

$$A_{f,t} = \max\left(0, \frac{R_{f,t}}{E_{f,t}^{in} + \epsilon}\right)$$

(High $A_{f,t} \Rightarrow$ unexplained energy, higher theft likelihood.)

Fuse vision + graph + energy anomaly (Bayesian-style or weighted logistic). A practical form:

$$C_k = \sigma\left(\alpha \operatorname{logit}(V_k) + \beta \operatorname{logit}(P_g(k)) + \gamma \operatorname{logit}(A_{z(k),t})\right)$$

- $A_{z(k),t}$: anomaly score for the zone/DT/feeder segment where event k lies
- α, β, γ: weights tuned on labeled enforcement outcomes
- $C_k \in [0, 1]$: enforcement confidence

E) Encroachment and Unsafe Construction Under Lines

Encroachment & 3D Corridor Intrusion Detection (CID-3D)

Using UAV RGB/orthomosaic ± LiDAR to flag unsafe encroachments under LT/11 kV lines.

Inputs: GIS centerlines/poles, UAV imagery, optional LiDAR

Outputs: Encroachment location, clearance gap, severity, action

Workflow:

- **Define corridor**
  - Create ROW buffer around feeder/LT lines using GIS standards.
- **Detect objects (RGB)**
  - Segment buildings, rooftops, cranes, trees, hoardings, construction stacks.
- **2D proximity check**
  - Measure object distance to line centerline.
  - Flag those within unsafe limits.

- **3D clearance check (LiDAR, if available)**
  - Classify ground, structures, vegetation, conductors.
  - Fit conductor curve and compute true 3D clearance and height violations.
- **Risk output**
  - Generate GIS layer with severity score and trigger safety work orders.

8. Gist Generation — Turning AI Findings into Field Actions

The goal is not to show raw detections, but to produce a clear, prioritized task list that answers: what to fix first, where, and why.

1) Severity Scoring

A scoring engine combines:

- Defect criticality (e.g., hotspot vs minor rust)
- Public and safety exposure (e.g., activity under live lines)
- Asset importance (feeder backbone vs LT spur)
- Trend over time and expected consumer impact
- This produces a transparent 0–100 priority score with reason codes that teams can trust.

2) Work-Order Mapping

Each defect type is linked to a ready action:

- Hotspot → tighten/replace + thermal retest
- Vegetation violation → trimming + clearance check
- Illegal tapping → enforcement + indexing correction
- Encroachment → safety notice + mitigation/line correction
- This enables direct flow into EAM/OMS with minimal manual interpretation.

3) Dashboards for Action

Leaders see:

- Feeder-wise defect heatmaps
- Top critical issues list
- Area-wise clusters of theft and ROW risks
- Focus stays on action, not analytics complexity.

9. Suggested Software stacks

a) Mission Planning & Field Ops

- UgCS — corridor scans, terrain follow, repeatable missions, KML/KMZ, RTK-ready, offline use
- QGroundControl — waypoint missions, geofencing, MAVLink logs, offline maps
- Emlid Reach (RS2+/M2) — RTK/PPK, NTRIP/RTCM, RINEX, cm-level accuracy, CORS support

b) Photogrammetry & LiDAR

- Agisoft Metashape — orthomosaic, DSM/DTM, dense cloud, RTK/GCP workflow
- CloudCompare + PDAL — LAS/LAZ processing, filtering, classification, QA/QC
- LAStools — fast ground/vegetation classification, corridor utilities

c) Data Lake & Storage

- MinIO (S3) — object storage, versioning, lifecycle tiers, encryption
- PostgreSQL + PostGIS — asset-linked metadata, spatial indexing

- OpenSearch — fast search across tags, OCR text, inspections

d) Processing & Orchestration

- Apache Airflow — scheduled ETL, retries, alerts
- Kafka (opt.) — event streaming for hotspot/theft alerts
- Spark (opt.) — large raster/vector batch processing

e) GIS & Web Mapping

- GeoServer — WMS/WFS/WMTS, raster+vector serving
- QGIS — QA/QC, editing, map packaging
- OpenLayers / Leaflet — web map UI, overlays, playback

f) AI/ML & MLOps

- PyTorch — model training (GPU)
- NVIDIA Triton — scalable inference (REST/gRPC)
- MLflow — experiment tracking, model registry
- Docker + Kubernetes — scalable, HA deployment

g) Annotation & Human QA

- CVAT — bbox/segmentation labeling, review flow
- Label Studio — quick classification/OCR checks

h) Security, API & Audit

- Keycloak — SSO, RBAC, MFA
- Kong / NGINX — API gateway, auth, logs
- Vault — secrets and key management

i) Monitoring & Operations

- Prometheus + Grafana — health, GPU/CPU, alerts
- ELK / OpenSearch Dashboards — centralized logs, audit trail

10. Cloud Computing Requirements (Sizing Logic)

Cloud capacity for UAV–AI use in DISCOMs should be based on actual mission load, not fixed VM numbers. A simple sizing view is:

D = Drones flying per day
M = missions per drone per day
V = avg data per mission (GB)

- RGB only: 40–70 GB
- RGB + Thermal: 70–110 GB
- RGB + Thermal + LiDAR: 120–180 GB

T_sla = inference turnaround (hours vs near-real-time)
R = retention (years)

Daily ingest:

$$G_{day} = D \times M \times V \quad (\mathrm{GB/day})$$

Annual storage before lifecycle tiering:

$$S_{year} = 365 \times G_{day} \times \eta$$

$\eta \approx 1.3-1.6$ (orthomosaic, DSM/DTM, point clouds, derivatives)

Workload	Dominant Resource	Examples
Ingest, checksum, metadata, tiling	**CPU + IO**	uploads, GeoTIFF pyramids, indexing
Photogrammetry / LiDAR processing	**CPU (bursty) + RAM**	stitching, classification
GIS serving / queries	**CPU + RAM**	WMS/WFS, spatial joins
AI inference (defects, thermal, ROW, theft)	**GPU (autoscale)**	detection/segmentation/fusion
Model training	**GPU (scheduled windows)**	weekly/monthly retrain

Table 10.1

Storage Sizing with Lifecycle

Tier	What lives here	Retention	Medium
Hot	last 30–60 days, active AI/GIS	fast access	S3/Blob (standard)
Warm	3–12 months	periodic access	S3 IA / cool tier
Cold	>1 year, compliance	rare access	Glacier / archive

Table 10.2

11. Governance, Security, and Compliance — Essential for DISCOM Operations

All DISCOM drone activities must fully comply with DGCA Drone Rules, 2021, related updates, and the DigitalSky framework. This covers flight permissions, registered drones, certified pilots, and strict adherence to green/yellow/red airspace zoning and geo-fencing norms.

Compliance should be written directly into RFPs, contracts, and SLAs—mandating DGCA-approved equipment, licensed operators, DigitalSky workflows, and respect for restricted zones. Making these clauses explicit reduces legal risk and supports audit-ready scaling.

Because drone outputs are used for safety, enforcement, and reporting, governance and security are foundational:

- Maintain a defensible evidence chain (hashing, immutable storage, audit logs)

- Enforce encryption in transit and at rest
- Apply RBAC so operators, analysts, and managers access only what they need
- Define clear data retention and lifecycle policies for operational vs legal records
- From an AI governance angle, models must be checked for bias across terrain, feeder types, and lighting conditions, with periodic review and retraining.

Severity scoring and work-order automation make this actionable: a multi-factor engine assigns a 0–100 priority score based on defect type, asset importance, public exposure, trends, and consumer impact. Rule templates then convert validated findings into standard work orders, ensuring consistent, traceable response across the DISCOM.

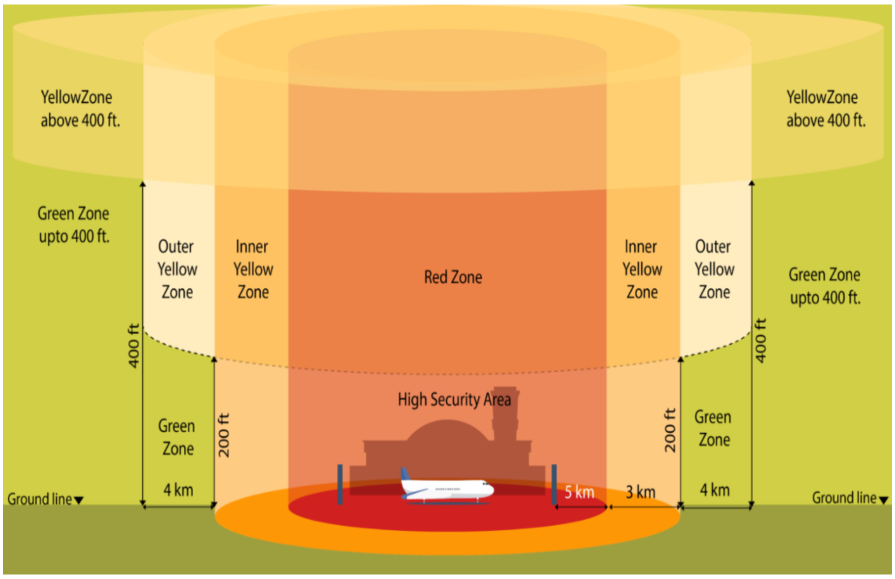

Fig 11.1

12. Dashboards for High Level Monitoring

AI insights are presented through executive dashboards built for quick, evidence-based decisions. They turn detailed inspection results into clear visuals such as feeder-wise defect heatmaps, clusters of theft or unauthorized loads, and ROW or clearance issues across areas.

These dashboards also show business impact—estimated loss recovery, revenue protection, and outages avoided through early hotspot and vegetation action. By tying technical findings to financial and reliability outcomes, leaders can prioritize investments, allocate resources wisely, and track the real value of drone- and AI-based inspections.

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Fig 12.1

13. Suggested MPPKVVCL Rollout Model

The rollout for MPPKVVCL is planned in phases to deliver quick results first and then scale into full enterprise integration.

Phase 1 — Rapid Value Pilot (8–12 weeks)

Focus on select critical 11 kV feeders:

- Thermal and RGB drone inspections for hotspots, defects, and safety risks
- DT hotspot audits for overloads and loose connections
- Identification of ROW risks like vegetation and clearance issues
- Limited consumer indexing pilot to validate RTK/PPK accuracy and GIS linkage

Phase 2 — Scale & Integration (3–6 months)

Expand across feeders and divisions:

- Full GIS-based corridor mapping and vegetation analytics
- Network-wide consumer–DT–feeder indexing
- Automated flow from defect detection to work-order closure in enterprise systems

This phased approach moves MPPKVVCL from a validated pilot to a sustainable, enterprise-grade drone and AI inspection program.

14. Cost Benefits Analysis

Adopting a drone-, AI-, and GIS-enabled inspection approach brings layered benefits across revenue, operations, safety, governance, and workforce use—creating both quick wins and long-term value.

Revenue

- Precise detection of theft, unauthorized loads, and billing gaps
- Better consumer–asset mapping and reduced AT&C losses

Governance & Compliance

- Geo-tagged, auditable inspection records
- Strong evidence for audits, vigilance, and regulatory reporting

- Data-backed capex/opex justification

Operations

- Faster feeder patrols and fault localization
- Quicker restoration and improved SAIDI/SAIFI
- Better control-room visibility

Maintenance & Asset Health

- Early detection of hotspots, damage, and vegetation risks
- Predictive maintenance and fewer unplanned outages
- Longer asset life and optimized maintenance cycles

Safety

- Reduced human exposure to live and hazardous conditions
- Early detection of unsafe encroachments and clearance issues

Manpower Optimization

- Shift from manual patrolling to focused rectification and preventive work
- Higher productivity with the same workforce

15. ROI(Return on Investment) & Case Study for one Distribution Center (Silua)

15.1 EZ DISCOM Hierarchy

EZ DISCOM

- 4 Regions: Jabalpur, Rewa, Sagar, Shahdol
- 22 Circles
- 60 Divisions
- ~560 Distribution Centres (DCs)

SILUA DC	
Parameter	**Value**
11 kV Lines	200+ km
33 kV Lines	46+ km
Distribution Transformers	1000+
Line Staff	11
Monthly Salary / Staff	₹15,000

15.2 Manpower Cost Baseline

$$C_{manpower} = N \times S \times 12$$

Where:

$N = 11$ staff, $S = ₹15,000$

$$C_{manpower} = 11 \times 15{,}000 \times 12 = ₹19.8\ \text{lakh/year}$$

Drone deployment reduces patrol dependency and redeploys staff from **search to rectification**, increasing productivity without proportional manpower expansion.

15.3 '11 kV' Feeder Breakdown Loss

Given:

- 1 breakdown/day
- Average duration = 3 hours
- Drone fault localization = 15 minutes

$$\Delta t = 3 - 0.25 = 2.75 \text{ hours/day}$$

Annual recovered outage time:

$$T_{rec} = 2.75 \times 365 \approx 1004 \text{ hours/year}$$

If:

- Average load = P_{11} MW
- Energy tariff = R ₹/kWh

$$Revenue_{11} = T_{rec} \times P_{11} \times 1000 \times R$$

15.4 '33 kV' Feeder Breakdown Loss

- 2 breakdowns/month
- Duration = 4.5 hours

$$\Delta t_{33} = 4.5 - 0.25 = 4.25 \text{ hours/event}$$

Annual recovery:

$$T_{33} = 2 \times 12 \times 4.25 = 102 \text{ hours/year}$$

Given higher feeder loading, recovered revenue per hour is significantly higher than 11 kV.

15.5 DTR Failure Avoidance Model

Let:

- Average DTR replacement cost = C_{DTR}
- Annual avoided failures = n

$$Savings_{DTR} = n \times C_{DTR}$$

Drone-based thermal and load sensing enables **pre-emptive load balancing**, reducing catastrophic transformer failures.

15.6 ROI Formulation

$$ROI = \frac{(R_{outage} + R_{DTR} + R_{theft} + R_{safety}) - C_{drone}}{C_{drone}}$$

Where:

- R_{outage} = revenue from avoided outages
- R_{DTR} = avoided asset failure cost
- R_{theft} = improved billing & enforcement
- R_{safety} = avoided compensation & legal cost

15.7 Cost–Benefit Summary (Silua DC)

Category	Impact
Fault localization time	Hours → minutes
Energy sold	Increased
DT failures	Reduced
Patrol manpower	Optimized
Safety incidents	Reduced
AT&C losses	Improved
Data quality	GIS-verified

16. International Benchmarking

USA — Scaling with BVLOS & Compliance Automation

Pacific Gas and Electric Company: Expanded UAV use for wildfire and storm response under its EPIC program, progressing toward BVLOS operations.

Key takeaway: Managing compliance, logs, waivers, and maintenance tracking is as critical as the drone hardware.

UK / Europe — Industrialized Inspection & Governance

National Grid (VICAP): BVLOS drone capture with AI-based corrosion assessment of pylons; drones replacing scaffolding and cherry pickers.

UK Power Networks (“Above and Beyond”): Trials using drones instead of helicopters for overhead inspections.

European Union Aviation Safety Agency: SORA risk framework for approving BVLOS and complex drone operations.

What to adopt: SORA-style safety case, standard mission templates, AI condition scoring linked to asset registry.

Australia — Drone Inspection as Routine Practice

Ausgrid: Regular drone inspections for poles, lines, and LiDAR-based tower surveys.

Endeavour Energy with Neara: LiDAR-driven digital twin for clearance checks and planning.

Civil Aviation Safety Authority: Clear BVLOS operational guidelines enabling scale.

Key insight: Treat drones as standard utility tools, backed by strong regulatory clarity and digital-twin integration.

17. Conclusion and Future Work

Integrating drones with AI and enterprise utility systems fundamentally changes how distribution networks are managed. What was once manual and reactive becomes data-driven, predictive, and operationally efficient.

Drones shorten fault-finding time, improve asset visibility, and enable early intervention. AI turns aerial images, thermal data, and geospatial inputs into clear actions—severity scores, work-order suggestions, and revenue-aware priorities.

The impact is both operational and financial: fewer outages, better protection of critical consumers, early detection of transformer stress, improved billing through accurate consumer indexing, and smarter use of field staff. Safety also improves as inspections shift away from hazardous conditions, while geo-tagged records strengthen compliance and governance.

Drones are no longer experimental tools; they are becoming essential cyber-physical assets for modern DISCOM operations.

Future Work

- Key areas for advancement include:
- Evolving AI models: Self-learning, multi-modal models using RGB, thermal, LiDAR, and AMI data
- Edge analytics: Near real-time defect detection during field operations
- AMI & load forecasting integration: Using asset health data to prevent overloads
- AI-based inspection scheduling: Dynamic planning based on risk and asset criticality
- Digital twins: Using drone data to simulate faults and plan network expansion
- Standards & scalability: Developing regulatory, procurement, and benchmarking frameworks for wider adoption

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