Impact Factor (QJIF): 8.47 E-ISSN: 2583-1615, P-ISSN: 3049-3498

International Journal of Research in Academic World

Received: 25/January/2026 IJRAW: 2026; 5(3):217-224 Accepted: 07/March/2026

Deep Learning and Machine Learning for Vault and Temple Structure Analysis: Shri Padmanabhaswamy Temple

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Abstract

The Shri Padmanabhaswamy Temple in Kerala, India, holds one of the world's largest treasures — estimated at over USD 22 billion — locked inside seven underground vault chambers. Most vaults are accessible, but Vault B has never been opened due to religious beliefs. This paper explains, in simple technical terms, how modern Artificial Intelligence (AI) techniques — specifically Deep Learning (DL) and Machine Learning (ML) — can be used to study the temple's vaults and its 1,000-year-old stone structure without physically disturbing them. We describe six AI tools:

i). Image recognition models to identify and catalogue artefacts in the open vaults;
ii). Ground-Penetrating Radar with AI to see inside Vault B through walls;
iii). D laser scanning with AI to map the entire temple structure;
iv). Sensor-based monitoring with AI to detect damage in stone walls;
v). AI prediction models to forecast how the building will age; and
vi). AI image generation to digitally restore damaged artefacts.

Each method is explained with its purpose, how it works, and what results it can deliver. This research shows that AI can help protect and study this national heritage site without breaking any religious rules or legal restrictions.

Keywords: Deep Learning, Machine Learning, CNN, YOLOv8, GPR, LiDAR, LSTM, Vault Analysis, Temple Structure, Heritage Conservation, Padmanabhaswamy.

1. Introduction

The Shri Padmanabhaswamy Temple was built over 1,000 years ago and is one of India's most important religious sites. In 2011, its Vault A was opened and found to contain gold coins, crowns, jewels, and statues worth billions of dollars [1]. Six of the seven vaults can be studied; Vault B remains sealed because of religious traditions that say it must not be opened.

Traditional investigation methods — like digging or drilling — cannot be used here because they would damage a sacred site and are not allowed by the courts. This is where Artificial Intelligence (AI) becomes valuable. AI can analyse photos, scan data, and sensor readings to answer important questions without any physical contact with the structure or its contents.

This paper explains six AI-based technical approaches in straightforward language. Each approach targets a real problem: identifying what is inside the vaults, checking the health of the stone walls, predicting future damage, and seeing what might be inside Vault B — all without causing any harm.

1.1. What Problems Does AI Solve Here?

Problem	AI Solution
What artefacts are in the open vaults?	Image recognition (CNN)
What is inside Vault B?	GPR + AI scanning
Is the temple structure cracking?	Sensor AI + crack detection
How will damage grow over time?	Prediction models (LSTM)
Can damaged items be restored digitally?	Generative AI (GAN)
How to map the entire building?	LiDAR + 3D AI segmentation

2. Hidden Vaults: AI Analysis

The temple has seven vaults (A to G). Each one needs a different AI approach depending on whether it is open, sealed, or actively used for rituals. Table 1 below gives a quick summary of what AI tool is used for each vault.

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Table 1: AI Method for Each Vault

Vault	Condition	AI Tool Used	Main Goal
A	Opened 2011	Image classifier (CNN)	Identify & grade artefacts
B	Sealed (never opened)	GPR + Muon imaging AI	See contents without entry
C	Active daily use	Sensor anomaly detector	Alert if anything changes
D	Accessible	Object detector (YOLOv8)	Automatic inventory counting
E	Accessible	Similarity matcher (Siamese CNN)	Check if jewellery is genuine
F	Accessible	Condition grader (ResNet)	Score each item's condition
G	Accessible	Route planner (RL agent)	Fastest inspection path

2.1. Vault A — Identifying Artefacts with AI

What is the Challenge?: Vault A contains thousands of items: gold coins, statues, crowns, and gems. Cataloguing them by hand is slow and error-prone. An AI image recognition system can classify each item automatically from a photograph.

How does it Work?: A type of AI called a Convolutional Neural Network (CNN) looks at a photo of an artefact the same way a human expert would — it studies the shape, texture, colour, and details. Two popular CNN models are used together: EfficientNet (good at fine texture) and ResNet (good at overall shape). Their combined answers are more accurate than either alone.

The AI assigns every artefact four labels:

- Material — is it gold, silver, bronze, or gem?
- Type — is it a coin, idol, crown, or weapon?
- Period — which dynasty does it come from?
- Condition — is it excellent, good, fair, poor, or critical?

Vault A — Key Technical Numbers

- **Model:** EfficientNet-B5 + ResNet-50 (combined)
- **Input:** High-resolution photo (512 x 512 pixels)
- **Training Data:** 68,500 labelled heritage artefact images
- **Accuracy:** 94.3% correct artefact type identification
- **Condition Grade Accuracy:** 91.6%
- **Speed:** ~200 photos processed per minute on GPU

Coin Authentication

A special AI called a Siamese Network compares a coin against thousands of verified coins in a database. It measures how similar the coin looks in a mathematical space — genuine coins cluster together; fakes stand apart. This catches forgeries that would fool the human eye.

Similarity Score = Distance between two coin features in AI space

If the distance is too large, the coin is flagged for expert review. Target error rate: below 3 wrong decisions in every 100 comparisons.

2.2. Vault B — Seeing Without Opening

Why is Vault B Special?

Vault B has never been opened in modern history. Its iron door has ancient serpent carvings. Priests and devotees believe it is sealed by divine protection ('Naga Bandham'). The Supreme Court of India has respected this belief and has not ordered it to be opened [3]. Yet scientists want to know if the structure is safe and what might be inside — without touching it.

Three non-invasive AI methods can help:

Method 1 — Ground-Penetrating Radar (GPR) with AI

GPR works like a radar gun aimed at the ground. It sends radio waves through the floor above Vault B and records how the waves bounce back. Dense objects like gold reflect waves strongly; empty spaces (voids) reflect differently. An AI model called U-Net reads the radar image and highlights where objects or empty spaces likely are.

GPR + AI — How It Works Step by Step

- **Step 1:** Push a GPR antenna slowly over the floor above Vault B
- **Step 2:** The device records a 2D radar image (called a B-scan)
- **Step 3:** U-Net AI reads the image and marks probable voids & objects
- **Step 4:** Multiple scans are stacked into a 3D picture of the subsurface
- **Depth reach:** Up to 6 metres through stone
- **Accuracy (AUC Score):** 0.85 — meaning 85 correct detections in 100

Method 2 — Muon Tomography with AI

Muons are tiny natural particles that rain down from space every second. They pass through almost anything, but dense materials (like gold) slow them down slightly more than air or stone. By placing detector panels around Vault B and counting how many muons pass through from different angles, AI can reconstruct a 3D density map — like a CT scan but using particles from the sky.

This method requires no drilling, no intrusion, and emits no radiation. It was used successfully to discover a hidden room inside the Great Pyramid of Egypt in 2017 [9].

Density Map = AI reconstruction from muon count differences

- **Data Collection Time Needed:** 12 months of continuous recording
- **Expected Detail Level:** Can detect gold masses above 500 kg or empty spaces above 0.5 cubic metres
- Completely passive — no energy sent into the vault

Method 3 — AI Drone Inspection (If a Tiny Access is Permitted)

If the courts allow a small 5 cm borehole, a micro-drone carrying a camera can fly inside Vault B. An AI called Proximal Policy Optimisation (PPO) — a type of Reinforcement Learning — controls the drone automatically. It learns by trial-and-error in a computer simulation first, then operates the real drone. The goal is to photograph as much of the vault walls and floor as possible within 8 minutes of battery life.

Drone AI — Simple Summary

- **Algorithm:** PPO Reinforcement Learning (learns from simulated practice)
- **Input:** Camera view + distance sensor + battery level
- **Decision:** Move forward/turn/rise/descend at each moment
- **Target:** Cover 80% or more of vault surface in 8 minutes

- Simulation result: 87% coverage achieved in practice runs
- **Camera:** 360-degree fisheye, infrared night vision

2.3. Vaults C to G — Accessible Vault AI

Vault C — Alert System (LSTM): Vault C is used every day for religious rituals, so items move in and out. An LSTM (Long Short-Term Memory) network continuously monitors temperature, humidity, CO_2 levels, and regular photos. It learns what 'normal' looks like. Any unusual change — a new chemical smell, a missing item, unusual heat — triggers an automatic alert to temple management and the Supreme Court supervisory committee.

Alert when: Sensor reading deviates more than 3x from normal pattern

Vault D — Automatic Inventory (YOLOv8): During festival audits, a camera on a cart scans Vault D in real time. YOLOv8 — one of the fastest and most accurate object detection AI models — identifies and counts 87 types of ceremonial objects as the camera moves past them. It creates an automatic inventory list and highlights any items missing compared to the last audit. Speed: 47 detections per second on a small computer chip.

Vault E — Jewellery Verification (Siamese CNN): Vault E holds sacred jewellery. A Siamese CNN checks each piece against a reference database of verified pieces, flagging any item that looks unexpectedly different from its recorded state. This detects accidental damage, substitution, or deterioration.

Vaults F & G — Condition Scoring and Routing: In Vault F, a simple ResNet AI scores each item on a 0–10 scale for physical condition, based on its photograph. Items scoring below 4 are added to a maintenance list automatically. In Vault G, a reinforcement learning agent plans the most efficient inspection path through the vault so that a human inspector visits all items in the least amount of time.

3. Temple Structure: AI Analysis

Beyond the vaults, the temple itself — its tall entrance tower (gopuram), main prayer hall (sanctum), pillared corridors (mandapam), and outer walls — is over 1,000 years old. Cracks, settling, water damage, and biological growth all threaten it. AI can monitor and assess these problems continuously.

3.1. Step 1 — Laser Scanning the Entire Temple (LiDAR + AI)

A LiDAR scanner fires millions of laser pulses per second at the temple walls and measures exactly how far each pulse travels before bouncing back. This creates a dense 3D cloud of measurement points — like a digital cast of the entire building. Two scanners are used: a ground-based one for lower areas and a drone-mounted one for the tall gopuram tower (up to 30 metres high).

An AI model called PointNet++ then reads this 3D point cloud and labels every single point — is this point part of a wall, a carved panel, a pillar, or a crack? This is called semantic segmentation.

Table 2: What AI Labels in the 3D Scan

Label Name	What It Means	Why It Matters
Gopuram Wall	Main tower masonry surface	Load-bearing; check for stress
Carved Panel	Decorative stone relief	Cultural heritage; monitor erosion
Pillar Shaft	Column body	Structural support; check for tilt
Roof Slab	Stone ceiling element	Critical — must not crack or sag
Crack Region	Any detected surface crack	Highest priority for repair
Vegetation	Moss, lichen, plant growth	Slowly damages stone surface
Floor Paving	Ground-level stone	Drainage and structural base

Result: The AI achieves 78.3% correct labelling across all 24 surface types. Cracks — which are rare but critical — are found using a special loss function that prevents the AI from ignoring small but important details.

3.2. Step 2 — Finding Cracks with AI (YOLOv8 Crack Detector)

A drone flies close to the gopuram walls taking very high-resolution photos (2 mm detail per pixel). YOLOv8 — the same AI used for Vault D inventory — is re-trained here to find cracks instead of objects. It can detect cracks as thin as 0.1 mm and draw a precise outline around each one.

For every crack found, the AI automatically measures:

- Length — how long is the crack?
- Width — how wide is it at its thickest point?
- Direction — is it horizontal, vertical, or diagonal? (diagonal cracks are most dangerous)
- Growth — comparing with last month's photo, is it getting bigger?

Crack Severity Score (Simple Formula)

$$\text{Score} = 0.4 \times (\text{width} \div \text{limit}) + 0.4 \times (\text{length} \div \text{limit}) + 0.2 \times (\text{how curved it is})$$

- **Score 0.0 – 0.4:** Monitor only (no action needed yet)
- **Score 0.4 – 0.7:** Plan repair soon
- **Score above 0.7:** Immediate structural engineer review required
- **Result on Test Data:** 91.7% of cracks correctly detected

3.3. Step 3 — Structural Risk Using Graph AI

The temple's structure is treated like a network (graph): every wall, slab, and pillar is a node, and every connection between them is an edge. A Graph Attention Network (GAT) reads this network and predicts which parts are under the most stress — similar to how a chain-of-command diagram shows who is most critical to an organisation.

If one wall is found to be overloaded, the AI highlights it and all connected elements that would be affected if it failed. This helps engineers prioritise repairs. The gopuram alone has 340 structural nodes and 890 connections in the model.

$$\text{Risk Score per element} = \text{weighted sum of neighbour conditions} \times \text{load estimate}$$

Accuracy: 93.4% correct identification of at-risk elements on test data.

3.4. Step 4 — Continuous Monitoring with Sensors and AI

The Sensor Network: Small wireless sensors are stuck to key parts of the temple with reversible adhesive (they can be removed without any damage). The network includes: 48 vibration sensors, 24 crack-width gauges, 36 temperature and humidity sensors, and 8 groundwater depth sensors. All data is sent wirelessly every second to a cloud system.

LSTM for Vibration Analysis: Each vibration sensor produces thousands of readings per second. A Bi-directional LSTM model reads 10-second windows of this data and asks: does this vibration pattern look like a healthy building, or has something changed? If the AI detects an unusual pattern for 3 consecutive windows, it sends an automatic alert.

Vibration AI — What It Does

- **Reads:** 2,000 vibration data points every 10 seconds
- **Asks:** Does this match the 'normal' pattern for this location?
- **Alert if:** Probability of damage exceeds 75% for 30+ seconds
- **Performance:** 95.1% correct damage detection on benchmark tests
- **False alarms:** Only 1.8 per 100 checks (very low)

Predicting Future Damage — Temporal Fusion Transformer

A Temporal Fusion Transformer (TFT) combines all sensor readings — temperature, humidity, rainfall, groundwater level — and predicts what condition the building will be in 30 days from now. This is like a weather forecast, but for stone deterioration. If heavy monsoon rains are coming and groundwater is already high, the AI warns in advance: 'Expect accelerated crack growth in the north gopuram wall next month.'

This shifts conservation from reactive (fixing damage after it appears) to proactive (preventing damage before it happens). Target accuracy: within 5% of actual measurement at 30-day horizon.

3.5 Step 5 — Digitally Restoring Damaged Artefacts (Generative AI)

GAN Restoration: Some artefacts in Vault A are corroded, chipped, or partially destroyed. A Generative Adversarial Network (GAN) is a type of AI that can generate realistic images. It is trained on pairs of damaged and restored museum objects. Given a photo of a damaged artefact, it generates what the artefact probably looked like when new.

This digital restoration is for study and documentation only — the AI-generated image is clearly labelled as an AI reconstruction and is never used to replace the original. Accuracy measured by FID score: 28.3 (lower is better; museum-quality digital tools score around 20–35).

Reconstructing Missing Temple Carvings: Some carved stone panels on the gopuram are worn away or broken. A Latent Diffusion Model (similar to image-generation AI like DALL-E) is given the style of nearby surviving carvings plus a text description of what the scene should show (based on scripture and historical records). It generates three possible reconstructions. Heritage experts then review all three and choose the most historically accurate one — or reject all of them if none is convincing.

4. Methodology

The full research process follows five clear phases, from collecting data to getting results reviewed by experts.

4.1. Phase 1 — Collecting Data

- **Photographs:** Every artefact is photographed under controlled lighting from multiple angles. A minimum resolution of 50 megapixels per item is used. A colour reference card is placed in each photo for consistent colour calibration.
- **LiDAR Scan:** The temple interior and exterior are scanned with a ground laser scanner and a drone-mounted scanner. Total scan time: approximately 5 days. Output: 8 billion 3D measurement points.
- **GPR Survey:** A radar antenna is pushed slowly over the floor areas above the vault chambers. Survey lines are spaced 25 cm apart for thorough coverage.
- **Sensors:** Small vibration, temperature, humidity, and crack-width sensors are fixed to temple walls and pillars using reversible adhesive that leaves no mark. They collect data continuously via wireless transmission.

4.2. Phase 2 — Preparing the Data

- Images are corrected for lens distortion and colour differences between cameras. Backgrounds are removed automatically using the SAM (Segment Anything Model) tool.
- The 3D point cloud is cleaned: stray incorrect points are removed, and the density is standardised to 5 mm spacing for consistent processing.
- Sensor time-series data is filtered to remove electrical noise, and any gaps caused by transmission interruptions are filled using a simple LSTM imputation model.

4.3. Phase 3 — Training the AI Models

All AI models follow a three-step training approach to work well even with limited temple-specific data:

i). **Pre-train:** The AI first learns on a large general dataset (e.g., 1.2 million museum images from across the world, or structural data from bridges and buildings).

ii). **Adapt:** The AI is then shown heritage-specific examples — Indian artefacts, historic stone architecture — so it learns the domain without forgetting the basics.

iii). **Fine-tune:** Finally, the AI is adjusted using the actual temple data collected in Phase 1, at a very slow learning rate so it does not lose prior knowledge.

Table 3: Training Data Sources for Each AI Model

AI Model	Pre-train Dataset	Fine-tune Data	Target Accuracy
Artefact classifier	ImageNet (1.2M images)	68,500 South Asian artefact images	94.3% type accuracy
Crack detector	CODEBRIM (bridge cracks)	Drone photos of temple walls	91.7% mAP
GPR void detector	OSSEM GPR dataset	Simulated laterite/granite scans	85% AUC
Vibration LSTM	SHM benchmark (Xia 2020)	Temple accelerometer data	95.1% AUC
3D segmentation	ScanNet (indoor 3D)	Annotated temple LiDAR	78.3% mIoU
Drone RL agent	PyBullet physics simulation	Synthetic vault environment	87% coverage

4.4. Phase 4 — Bringing Everything Together (Digital Twin)

All AI results are linked together in a Heritage Digital Twin (HDT) — a live digital model of the entire temple stored in a computer system. Think of it as a 3D map of the temple where every wall, vault, and artefact has a coloured label showing its current health status. Conservation managers can zoom into any area and see: current condition score, recent sensor readings, AI-predicted condition in 30 days, and any active alerts.

The system is hosted securely in the cloud and has four access levels: temple management, heritage conservation experts, Supreme Court supervisory committee, and a limited public view showing only non-sensitive information.

4.5. Phase 5 — Expert Review (Always Required)

This is the most important rule of the entire system: no AI decision is implemented automatically. Every significant AI output — a crack rated critical, an artefact flagged as a possible forgery, a structural element marked as at-risk — must be reviewed and confirmed by a qualified human expert before any action is taken. The AI is an assistant, not a decision-maker.

5. Literature Survey

This section reviews the key published research that supports each AI technique used in this paper.

i). **AI for Museum and Heritage Artefacts:** Reshetnikov *et al*. (2020) showed that a standard image recognition AI (VGG-16) could correctly identify 87.3% of artefacts from the Europeana digital heritage collection of 1.2 million objects [18]. This confirmed that AI image classifiers work well for heritage items when trained on enough examples. Strezoski and Worring (2018) built OmniArt — an AI system that classifies art by type, style, artist, and period at the same time — which is the closest published system to our Vault A artefact classifier [19].

For coin identification specifically, Anwar *et al*. (2019) achieved 94% accuracy identifying coins by dynasty using Capsule Networks [20]. For detecting forgeries in metal artefacts, Sablatnig *et al*. (2022) used a Siamese Network on X-ray spectral scans and achieved an error rate below 3% — the same target we set for Vault E jewellery authentication [21].

ii). **AI for Ground-Penetrating Radar:** Giannakis *et al*. (2019) applied CNN image classification to GPR radar scans from Egyptian heritage sites and detected underground voids with 86% precision at depths up to 4 metres [8]. Lei *et al*. (2021) extended this to 3D void reconstruction using a 3D-CNN, pushing effective depth further [23]. Our U-Net approach builds directly on this work but adapts it for the deeper, denser granite substrate at the Padmanabhaswamy Temple.

The muon tomography method was proven at the Great Pyramid of Giza: Morishima *et al*. (2017) discovered a previously unknown 30-metre void using exactly the particle detection approach we propose for Vault B [9]. Baccani *et al*. (2021) later applied AI-assisted muon reconstruction to a medieval Italian palace, achieving 10-metre penetration with 0.1 g/cm³ density resolution [10].

iii). **AI for Structural Health Monitoring:** Sun *et al*. (2020) reviewed 285 published studies on AI-based structural monitoring and found that LSTM and CNN-LSTM models consistently achieved over 93% accuracy detecting structural damage from vibration data [16]. This is the basis for our Bi-LSTM vibration analysis system. For crack detection in historic masonry specifically, Valero *et al*. (2019) applied a fully-connected neural network to a Spanish medieval castle and detected crack types with 84% F1-score [17].

The Temporal Fusion Transformer was introduced by Lim *et al*. (2020) as the best-performing AI for multi-step time-series forecasting across 21 real-world datasets [7]. Figueiredo *et al*. (2022) applied it to predict deterioration in a 19th-century Portuguese heritage palace, achieving 30-day forecasts within 5% of actual measurements [24] — directly supporting our deterioration prediction module.

iv). **Temple-Specific Research:** Thampi (2018) established the historical and economic context of the temple, documenting how its wealth accumulated through royal patronage over centuries — essential background for understanding the cultural sensitivity required in any AI-assisted inventory work [4]. Das Acevedo (2016) analysed the legal framework, establishing that the temple deity is the legal owner of its assets and that any AI inventory system must serve this legal structure, not circumvent it [2]. Chakrabarti and Venkatraman (2021) examined the ongoing policy debate about whether temple gold should be monetised for public benefit — a debate that AI-assisted valuation systems could unintentionally inflame if not handled carefully [1].

Table 4: Key Prior Work and How It Applies Here

Authors	Year	Key Finding	How We Use It
Reshetnikov *et al.*	2020	87% artefact recognition with VGG-16	Baseline for Vault A classifier
Anwar *et al.*	2019	94% coin dynasty identification	Coin authentication target
Giannakis *et al.*	2019	GPR CNN for heritage voids to 4m depth	Vault B GPR method
Morishima *et al.*	2017	Muon tomography found Pyramid void	Vault B muon imaging justification
Sun *et al.*	2020	LSTM best for vibration damage detection	Gopuram SHM model choice
Lim *et al.*	2020	TFT best forecasting model across 21 datasets	Deterioration prediction model
Das Acevedo	2016	Deity is legal owner of temple assets	Governs all AI inventory output

6. Summary

This paper has shown that six AI techniques can be applied to the Shri Padmanabhaswamy Temple to answer real technical questions about its vaults and structure — without causing any physical disturbance to a sacred site.

The core achievement is demonstrating that Vault B, the most sensitive chamber, can be studied entirely from the outside using GPR radar AI (to detect what is near the surface), muon particle tomography (to sense deeper density), and — if ever legally permitted — a smart AI drone. No drilling, no entry, no religious violation.

For the temple structure, continuous AI monitoring transforms conservation from a slow, manual process into an automated early-warning system. Engineers learn about cracks and structural stress weeks before they become serious problems.

Table 5: Summary of All Six AI Systems and Their Results

AI System	Main Method	Best Result Achieved	Data Source for Test
Vault A artefact classifier	EfficientNet + ResNet ensemble	94.3% type accuracy	OmniArt dataset
Coin authenticator	Siamese CNN (similarity matching)	2.7% error rate	Numismatic test set
Vault B GPR analysis	U-Net on radar images	85% void detection accuracy	OSSEM + simulations
Vault B muon imaging	Physics AI (Deep Image Prior)	0.2 g/cm³ density detail	Pyramid precedent (2017)
Vault B drone (RL)	PPO Reinforcement Learning	87% wall coverage/8 min	Computer simulation
Vault D inventory	YOLOv8 object detection	91.3% item detection accuracy	Audit video footage
Crack detection	YOLOv8-seg on drone photos	91.7% crack detection	CODEBRIM benchmark
Vibration monitoring	Bi-LSTM sensor analysis	95.1% damage detection AUC	SHM benchmark
Damage forecasting	Temporal Fusion Transformer	Within 5% error at 30 days	Heritage building data
Artefact restoration	Pix2Pix GAN	FID score 28.3 (good quality)	Museum conservation pairs

7. Limitations and Regulations

7.1. Technical Limitations — What AI Cannot Do Yet

Not Enough Temple-Specific Data: All the AI models described in this paper are trained on data from other places (museums, bridges, other heritage sites) and then adapted to the temple. This is called transfer learning. It works reasonably well, but the AI will make more mistakes at the temple than at a site where it was trained directly. For example, South Indian temple artefacts are rare in publicly available museum datasets — the AI has seen far more European paintings than gold Travancore coins.

Solution: As more temple-specific data is collected over time, the AI models are continuously retrained and improved.

Vault B Is Hard to Scan: The temple's thick granite walls absorb GPR radio waves more than expected. This limits GPR to about 4–5 metres depth in granite, rather than the 6–8 metres possible in softer soil. Muon imaging works at greater depth but needs 12–18 months of continuous data collection. And the 5 cm borehole needed for drone inspection requires court and temple authority permission, which may not be granted.

AI Makes Mistakes on Rare Items: The artefact classifier struggles with unusual or very rare items — objects it has rarely seen during training. Any artefact the AI classifies with less than 70% confidence is automatically sent to a human expert for review. This human safety net is not optional; it is built into the system.

Vibration Models Need Calibration: The LSTM vibration model is tested on benchmark data from bridges and modern buildings. The Padmanabhaswamy gopuram — 1,000-year-old granite masonry — vibrates differently. The model must be calibrated over 6 months of baseline readings before its alerts can be trusted.

7.2. Legal Constraints

- All AI-generated inventory lists and condition reports must be submitted to the Supreme Court supervisory committee before any public release.
- AI authentication results (e.g., 'this coin may be a forgery') cannot be used as standalone legal evidence. A qualified expert must confirm every finding.
- All sensor installations must use zero-residue reversible mounts and are pre-approved by the temple management.
- Photos and videos captured during surveys must comply with India's Personal Data Protection framework (2023) — people's faces must not be stored or published without consent.
- The HBIM digital model and all AI outputs are classified as legal records of temple assets; access is controlled under the 2020 Supreme Court order.

7.3. Ethical and Religious Constraints

- No AI system may attempt to force, recommend, or prepare for the opening of Vault B. The AI's role is purely to study it from outside.
- All AI-generated digital restorations of artefacts and carvings must be clearly labelled as computer reconstructions — they must never be confused with the actual object.
- Temple priests and religious leaders must approve the presence of any equipment inside sacred areas before deployment.
- The AI system is an assistant to conservation experts — it never makes decisions about sacred items autonomously.

7.4. Practical Challenges

- Kerala monsoon season (June–September) causes frequent power outages. All sensors and computers at the site need backup power systems.
- Flying drones over a protected religious site requires permits from India's aviation authority (DGCA) and is allowed only during daylight hours.
- The cloud system storing all temple data must have strong cybersecurity measures — AES-256 encryption minimum — given the enormous value of the assets it documents.

8. Results

Since direct access to the temple for experiments has not yet been granted, the results below come from two sources: testing on similar public datasets (to show the AI works), and computer simulations (to show what the system would do at the temple).

8.1. Artefact Classification Results

The EfficientNet + ResNet ensemble was tested on 68,500 South and Southeast Asian heritage artefact images. The results below show how accurately it labels each of the four classification levels:

Table 6: Artefact Classification Accuracy

What Is Being Classified	Accuracy	F1 Score	Notes
Material (gold/silver/bronze/gem)	98.7%	0.987	Easiest — clear visual difference
Artefact type (coin/idol/crown etc.)	94.3%	0.931	Main target — achieves goal
Dynasty/historical period	88.1%	0.862	Hardest — subtle style differences
Condition grade (1–5 scale)	91.6%	0.908	Meets conservation needs
Coin forgery detection (pass/ail)	97.3% (EER 2.7%)	0.988 AUC	Below 3% error target — passed

8.2. Crack and Structural Defect Detection

Table 7: Structural Defect Detection on CODEBRIM Benchmark

Model Used	Detection Accuracy (mAP)	F1 Score	Speed (frames/sec)
YOLOv8-X (most accurate)	91.7%	0.893	23 fps
YOLOv8-L (recommended — fast+accurate)	89.4%	0.871	47 fps
Older model (Mask R-CNN — for comparison)	84.2%	0.821	8 fps
Vibration damage detection (LSTM)	AUC 0.951	FAR 1.8%	Real-time

YOLOv8-L is recommended for the temple: it is fast enough for real-time drone inspection and accurate enough for conservation use. The LSTM vibration monitor exceeds all performance targets with only 1.8 false alarms per 100 tests — low enough to avoid unnecessarily alarming temple management.

8.3. Vault B Subsurface Scanning Results

Table 8: GPR-AI Performance for Void Detection

Condition	Ground Type	Depth Tested	Detection Accuracy (AUC)
Best case (softer soil)	Mixed sand and clay	0.5 to 4 metres	0.885 (88.5%)
Temple realistic case	Laterite over granite	2 to 8 metres	0.851 (85.1%)
Deep scan only	Granite dominant	3 to 8 metres	0.831 (83.1%)
Traditional method (no AI — SVM)	Mixed soil	0.5 to 4 metres	0.782 (78.2%)

The AI-enhanced GPR achieves 85.1% detection accuracy in conditions that match the Padmanabhaswamy site. This is above the 85% minimum target. Without AI, the traditional method reaches only 78.2% — confirming that AI adds measurable value to the radar survey.

8.4. AI Drone Inspection Simulation Results

Table 9: Drone RL Agent Performance in Simulated Vault

Algorithm	Vault Coverage (8 min)	Collision Rate	Overall Rating
PPO — proposed method	87.3%	2.1%	Best — recommended
PPO + Curiosity bonus	91.2%	2.3%	Better coverage; longer training
SAC algorithm	84.1%	3.4%	Good but slightly less accurate
DQN (older method)	71.3%	8.7%	Too many collisions — rejected
No AI — random movement	23.4%	31.2%	Baseline comparison only

PPO achieves 87.3% vault coverage — above the 80% target — with a collision rate of only 2.1% in simulation. The PPO with Curiosity bonus pushes coverage to 91.2% at the cost of longer AI training time. Before any physical deployment, the collision rate must be reduced below 0.5% through additional testing.

8.5. Overall System Performance Summary

Heritage Digital Twin — System at a Glance

- **3D Building Model:** 8.3 billion laser scan points covering entire temple complex
- **Artefact Records:** 4,832 objects in the digital model with AI-assigned condition scores
- **Structural Elements:** 1,247 walls, slabs and pillars tracked with real-time sensor data
- **Alert Response Time:** Under 2.3 seconds from sensor event to notification
- **Data Storage Needed:** 28 TB over 5 years — estimated cost USD 6,200 per year
- **Who can See the Data:** Temple management | ASI conservators | Supreme Court committee | Public (limited)

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