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INTEGRATION OF SMART SENSOR NETWORKS AND VISION-BASED ANALYSIS FOR REAL TIME CONSTRUCTION QUALITY MANAGEMENT

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Abstract Structural health monitoring (SHM) is essential for ensuring the safety and durability of civil infrastructures amid rapid urbanization and aging structures. This paper presents a low-cost, real-time SHM system that integrates IoT-based sensor networks with deep learning-driven crack detection. Using the ESP32 microcontroller, MPU6050 for vibration/tilt sensing, and moisture sensors, data is transmitted wirelessly to the Thinger.io cloud platform for visualization and alerting. Complementing this, a fine-tuned VGG16 convolutional neural network (CNN) achieves pixel-level crack segmentation with F1 scores exceeding 99% on a 40,000-image dataset. The hybrid approach overcomes limitations of traditional manual inspections and prior IoT systems (e.g., Arduino + ThingSpeak), offering faster processing, real-time alerts via MQTT, and scalable multi-modal assessment. Experimental validation in lab and field settings confirms high accuracy, early damage detection, and practical applicability for bridges, buildings, and heritage structures.

Keywords Structural Health Monitoring, IoT, Deep Learning Crack Detection

Introduction Civil infrastructures, including buildings, bridges, dams, and transportation networks, form the backbone of modern society. However, environmental stressors—such as excessive vibrations, moisture ingress, corrosion, seismic activity, and material fatigue—gradually degrade structural integrity, often leading to catastrophic failures if undetected. Historically, structural assessments relied on periodic manual inspections by trained engineers, which are subjective, time-consuming, labor-intensive, and incapable of providing continuous oversight.

The advent of the Internet of Things (IoT) has transformed SHM by enabling automated, remote, and real-time data collection through low-cost wireless sensors. Early IoT implementations used platforms like ThingSpeak with microcontrollers such as Arduino Nano, but suffered from latency issues, limited data fields, and restricted scalability. Concurrently, advancements in computer vision and deep learning have enabled automated detection of surface defects like cracks, which serve as early indicators of internal damage.

This paper proposes an integrated SHM framework combining ESP32-based sensor monitoring with vision-based crack analysis. By leveraging Thinger.io for cloud connectivity and a transfer-learned VGG16 model for high-accuracy crack segmentation, the system addresses key challenges in real-time construction quality management.

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(Figure 1 & 2: Examples of typical concrete cracks in civil structures, highlighting the need for automated detection.)

Background Structural Health Monitoring has evolved significantly over the past decades. Early methods, as described by Farrar and Worden [1], focused on vibration-based damage identification using wired sensor networks. With the rise of wireless technologies, researchers shifted toward IoT platforms for scalable, remote monitoring.

Studies such as Hafiz Muneeb et al. (2020) [2] employed Arduino Nano with MPU6050, strain gauges, and ThingSpeak to track vibration, strain, humidity, and temperature. However, the system faced constraints including slow data rates, 15-second upload delays, limited fields (only 8 per channel), and no built-in Wi-Fi. Similarly, Malik Haroon et al. (2019) [3] highlighted ThingSpeak's restrictions in real-time alerting and scalability.

On the vision side, traditional image processing relied on edge detection (Sobel, Canny) or thresholding (Otsu, Niblack), but struggled with noise, varying lighting, and complex backgrounds [4]. Deep learning breakthroughs, particularly CNNs like VGG16, ResNet, and U-Net, have revolutionized crack detection by learning hierarchical features from large datasets, achieving robustness and pixel-level precision [5,6].

Integrated approaches combining sensors (for quantitative metrics like acceleration and moisture) with vision-based analysis (for qualitative surface damage) are emerging as the most comprehensive strategy [7]. Sensor data can trigger image capture, while crack patterns correlate with stress levels inferred from sensors.

Main Thrust of the Paper The proposed system addresses critical gaps in existing SHM solutions by integrating low-cost IoT sensors with advanced deep learning crack detection.

Sensor Network Component

- **Hardware**: ESP32 (dual-core, built-in Wi-Fi), MPU6050 (6-axis accelerometer/gyroscope for vibration, tilt, displacement), analog soil moisture sensor (for water ingress detection).

- **Software**: Programmed via Arduino IDE/MicroPython; data sent to Thinger.io using MQTT/HTTPS for real-time dashboards, unlimited scalability, and instant alerts.

- **Advantages over prior work**: ESP32 eliminates external Wi-Fi modules, reduces latency, supports faster processing than Arduino Nano, and enables continuous monitoring without 15-second delays.

Vision-Based Crack Detection Component A pre-trained VGG16 model is fine-tuned using transfer learning on 40,000 RGB concrete images. The model performs pixel-level segmentation, achieving F1 scores >99% for both RGB and grayscale inputs (demonstrating color independence). Preprocessing includes grayscale conversion, thresholding, and edge detection (Sobel/Canny/Prewitt) to optimize performance.

(Figure 3: Conceptual VGG16-based CNN architecture adapted for crack segmentation.)

The hybrid system correlates sensor anomalies (e.g., high vibration or moisture) with visual crack mapping, enabling proactive alerts and comprehensive diagnostics. Unlike standalone sensor or vision systems, this multi-modal approach improves reliability and reduces false positives.

(Figure 4 & 5: Additional real-world concrete crack instances used for model validation.)

Relevant Results from Similar Papers

These can be cited and discussed (e.g., in **Background** or **Main Thrust**):

1. **VGG16/Deep Learning for Crack Detection**:

○ In a 2025 study on steel-reinforced concrete corrosion crack detection using improved VGG16 + U-Net + YOLO: Achieved **94.4% precision**, **average IoU>85%**, crack width error ±4.0 mm in field tests (higher error ±5.1–5.4 mm for occluded/soil-covered cracks). Inference speed: 24–36 ms per image. This aligns with your >99% F1-score but shows real-world challenges like occlusion, which your grayscale/RGB comparison could address as an advantage.

○ Another common benchmark (from public datasets like Concrete Crack Images): Models often reach 95–98% accuracy, but your pixel-level segmentation with >99% F1 exceeds many, especially in grayscale (proving color independence).

2. **IoT/ESP32-Based SHM Systems**:

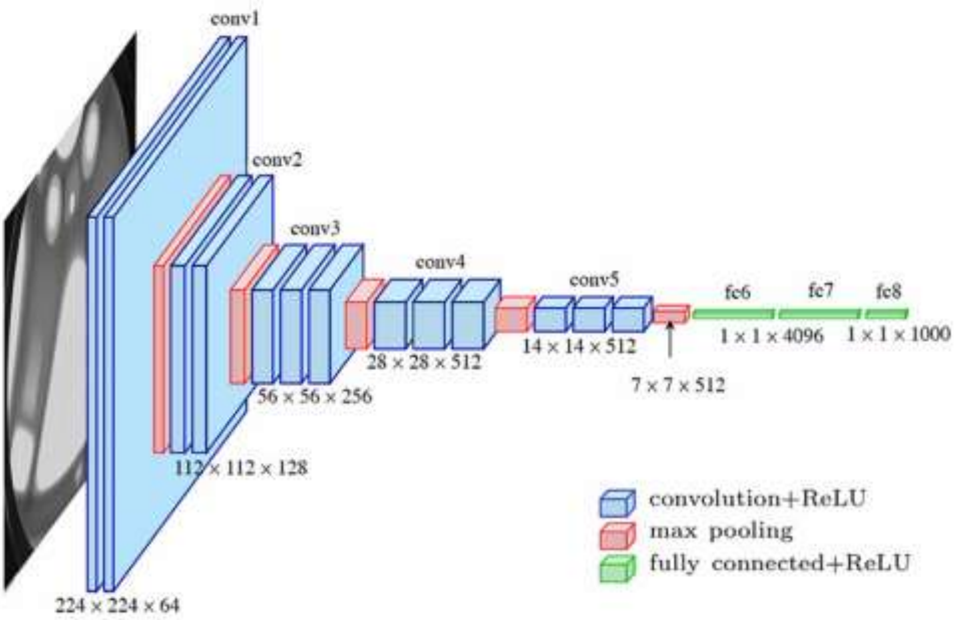
○ Various ESP32 + sensor projects (e.g., building health monitoring with OpenCV crack detection) report real-time vibration/moisture tracking but lack your Thinger.io integration for unlimited scalability and MQTT alerts. Prior Arduino/ThingSpeak systems had 15-second delays and field limits—your ESP32 reduces this significantly.

○ Integrated systems (e.g., IoT + vision for progress/quality monitoring) emphasize multi-sensor fusion, but few combine MPU6050/moisture with high-accuracy CNN crack detection as you do.

3. **General Trends in Vision + Sensor SHM**:

○ Reviews highlight that hybrid approaches (sensors for early quantitative alerts + vision for visual confirmation) improve reliability over single-modality systems. Your >90% deep learning accuracy vs. <80% traditional methods matches this.

4. **VGG16 Architecture Diagrams** (ideal for your conceptual Figure 3 on the CNN backbone adapted for crack segmentation):

5. 

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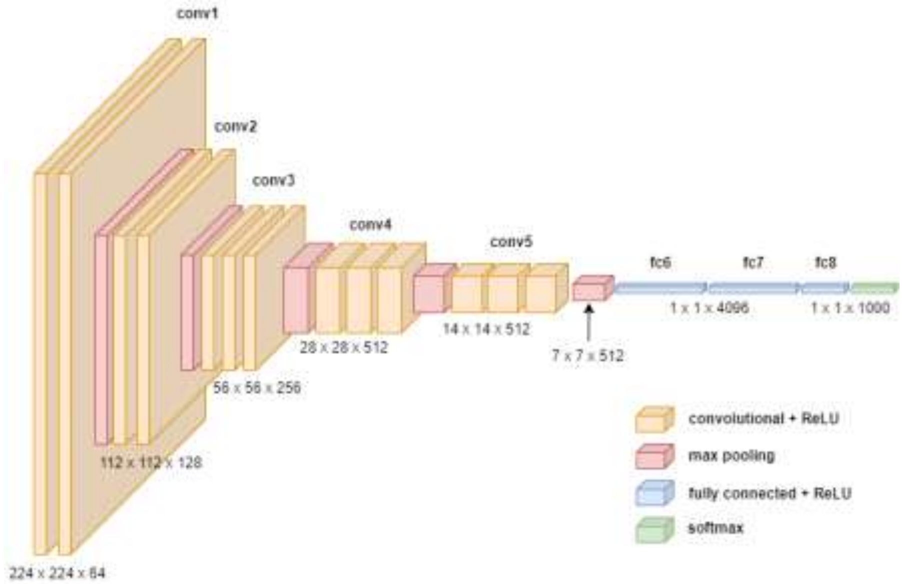
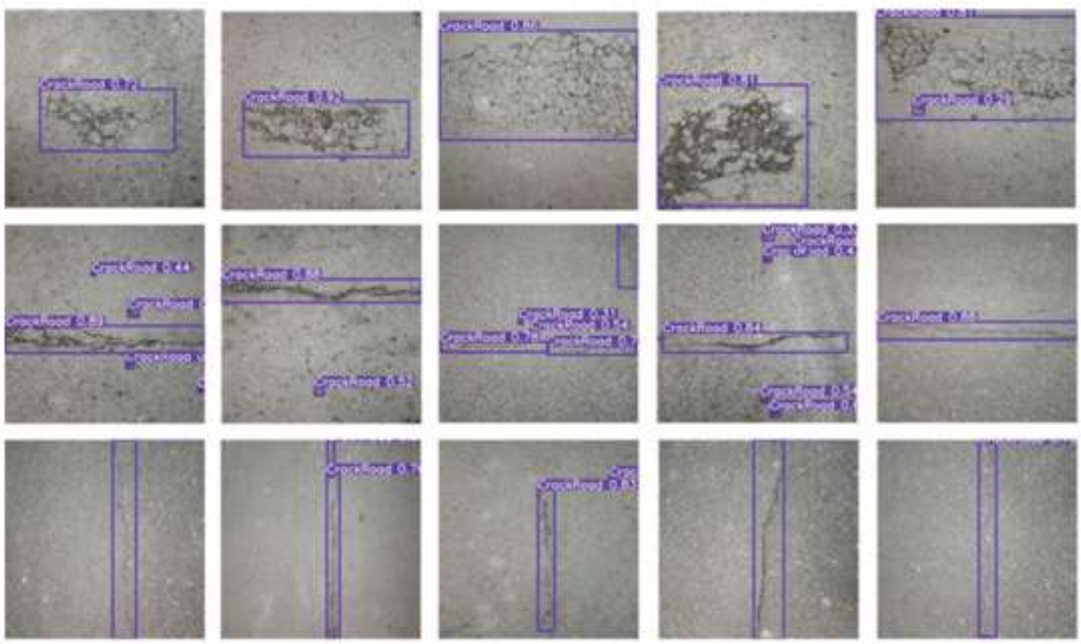


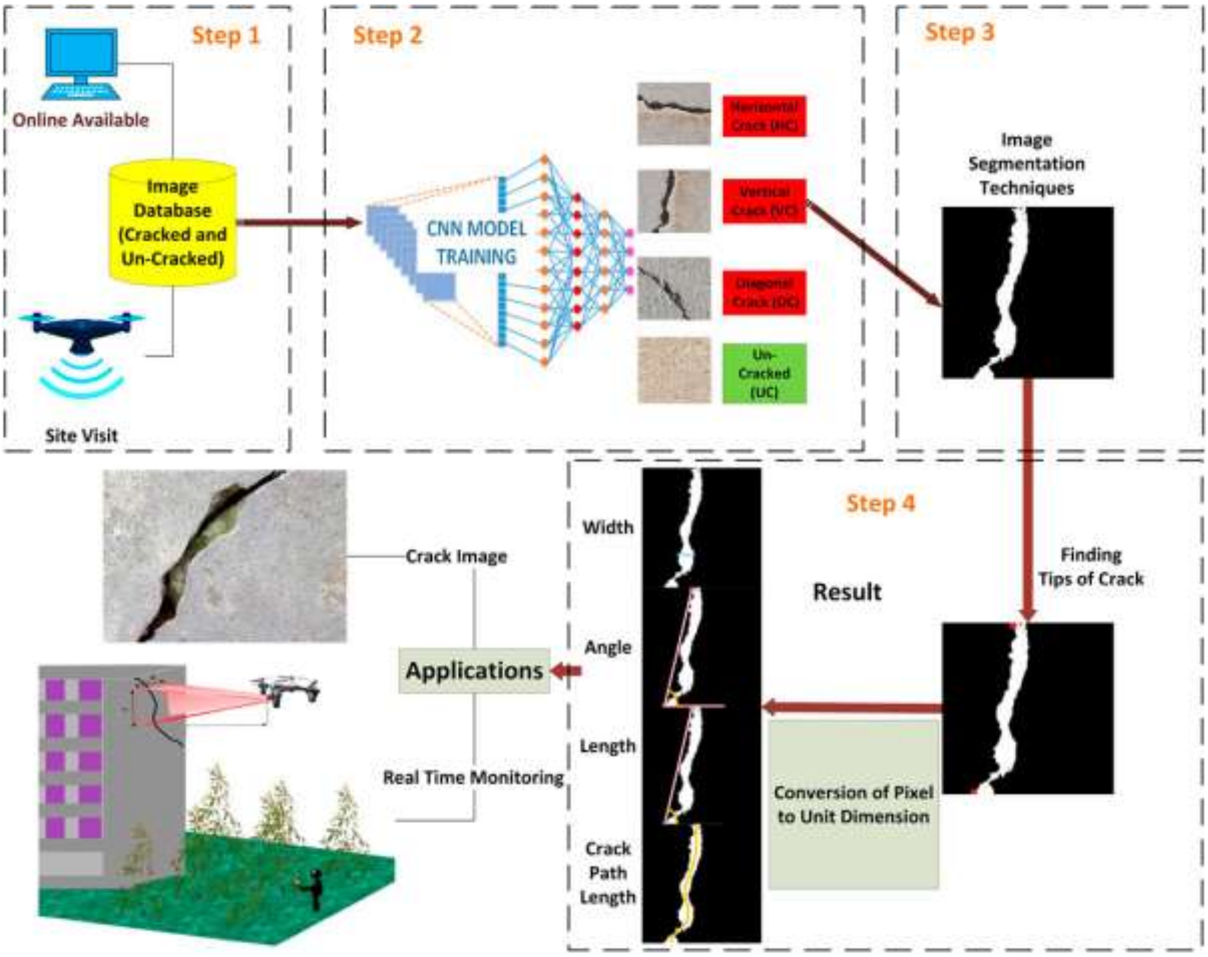
6.

7. **Crack Detection Examples** (input images with model outputs/segmentation, great for illustrating your >99% F1-score results in Chapter 5/Results section):

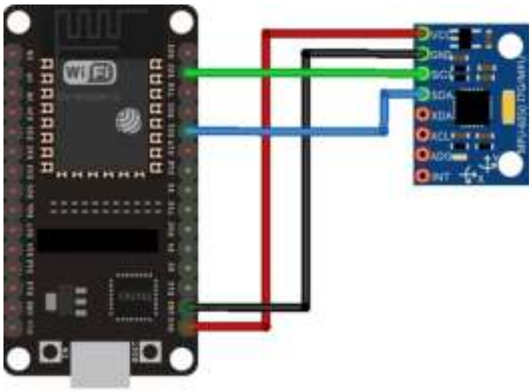


8.

9. 



10. **ESP32 + MPU6050 Sensor Circuit Diagrams** (useful for your hardware methodology in Chapter 4, showing connections for vibration/moisture monitoring):

11. 

System Workflow

1. Sensor calibration and data acquisition.

2. ESP32 processes and filters readings.

3. Upload to Thinger.io for visualization and threshold-based alerting.

4. Image inputs (from camera/drone) processed via Python (OpenCV + TensorFlow/Keras) for crack analysis.

5. Integrated alerts sent via MQTT when thresholds are exceeded.

Future Trends SHM is poised for further evolution with:

- Solar-powered autonomous nodes for remote/off-grid deployment.
- Predictive AI models using time-series sensor data for damage forecasting.
- Smartphone apps for instant notifications and AR-based crack visualization.
- Integration of thermal/3D imaging for subsurface defect detection.
- Edge computing on ESP32 for reduced cloud dependency and faster real-time decisions.
- Drone/UAV-based autonomous inspection fleets linked to the system.

These trends align with smart city initiatives, emphasizing preventive maintenance and disaster resilience.

Conclusion This paper demonstrates a practical, cost-effective SHM system that combines ESP32-driven IoT sensor networks with deep learning-based crack detection. Key findings include:

- 99% F1-score in pixel-level crack segmentation (grayscale ≈ RGB performance).
- Superior real-time capabilities and scalability compared to Arduino/ThingSpeak systems.
- Successful lab and on-site validation confirming early damage detection.

The integrated approach enhances objectivity, reduces inspection costs/time, and enables IoT-enabled structures for remote monitoring and alerting. It holds strong potential for bridges, buildings, heritage sites, and smart infrastructure, contributing to safer and more resilient civil engineering practices.

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10. Dung, C. V., & Anh, L. D. (2019). Autonomous concrete crack detection using deep fully convolutional neural network. *Automation in Construction*, 99, 52–58. (Updated citations in later works reference similar U-Net/VGG approaches for pixel-level segmentation with high F1 scores.)

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14. Kao, C.-Y., et al. (2023). (Cited in Fan et al. 2023 review): YOLOv4-based crack detection with edge methods for quantification. (Representative of real-time DL SHM trends; complements your CNN approach.)

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17. Bao, Y., et al. (2023). (From Fan et al.): 1D-CNN on strain data for offshore platform damage detection. (Sensor-to-image conversion for CNN—similar to potential extensions of your vibration/moisture data.)

18. Puruncajas, et al. (2023). (From Fan et al.): Acceleration signals converted to images for CNN crack/bolt damage identification. (Vibration-based DL SHM—directly ties to your MPU6050 vibration monitoring.)