Wildfire Prediction Using Real-Time Geospatial Data and Machine Learning

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Certificate

This is to certify that the dissertation report entitled **Wildfire Prediction Using Real-Time Geospatial Data and Deep Learning** submitted by Hitanshi Patil (16010122283), Harikrishnan Gopal (16010122284), Maurya Ghogare (16010122285) and Sanika Pendurkar (16010122286) at the end of semester VIII of LY B. Tech is a bona fide record for partial fulfillment of requirements for the degree Honours in Data Science and Analytics (**Offered by Department of Computer Engineering**) of Somaiya Vidyavihar University

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Abstract

Wildfires pose a significant threat to forests, wildlife, property, and human life, with over half of India's forest area being fire-prone. Traditional detection methods including human observation and satellite monitoring suffer from delays, inconsistency, and limited coverage, particularly in remote and hilly terrains. This thesis presents a comprehensive deep learning-based wildfire detection system that addresses the critical trade-off between accuracy and computational efficiency for real-world deployment.

The research systematically evaluates twelve deep learning architectures through a four-stage training pipeline: baseline transfer learning, fine-tuning, specialized FireNet implementation, and a novel custom architecture. Transfer learning models including VGG16, VGG19, ResNet50, ResNet50V2, EfficientNetB0, and MobileNetV3 variants were initially evaluated, achieving baseline accuracies between 83.62% and 95.41%. Fine-tuning the top three performers improved accuracies by 3-5%, with VGG19 reaching 99.17% accuracy.

The primary contribution of this work is WildfireNet, a custom lightweight convolutional neural network incorporating residual connections, channel attention, and spatial attention mechanisms. WildfireNet achieves 98.84% accuracy with only 5.1 million parameters, representing a 28× reduction compared to VGG19 while maintaining comparable performance. The model demonstrates strong metrics across all evaluation criteria: AUC of 0.9991, F1-score of 0.9883, precision of 0.9879, and recall of 0.9887.

Comparative analysis reveals that generic lightweight architectures like MobileNetV3 and EfficientNetB0 struggle with wildfire-specific features, achieving only 83-86% accuracy due to aggressive feature compression and lack of attention mechanisms. The research conclusively demonstrates that wildfire detection requires specialized architectures rather than off-the-shelf solutions. WildfireNet's compact design makes it suitable for edge deployment on IoT devices, drones, and surveillance cameras, enabling real-time automated wildfire detection in remote forest regions. The system shows significant potential for integration into national forest monitoring infrastructure, offering faster response times and reduced damage from wildfire incidents.

Keywords*: Wildfire Detection, Deep Learning, Convolutional Neural Networks, Transfer Learning, Attention Mechanisms.*

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Chapter 1
Introduction

This chapter provides an overview of the wildfire detection problem, establishing the background context of increasing wildfire incidents in India and globally. It discusses the limitations of traditional detection methods and articulates the motivation for developing an automated, AI-based detection system. The chapter concludes by defining the scope and organization of the thesis work.

1.1 Introduction

Wildfires have emerged as one of the most devastating natural hazards, capable of destroying vast forest landscapes, displacing wildlife, damaging property, and endangering human life within minutes. In recent years, the increasing impact of climate change manifested through rising temperatures, prolonged dry seasons, and extreme weather events has amplified both the frequency and intensity of wildfire incidents across the world, including India. As a result, forests that were once considered low-risk are now experiencing recurring fire outbreaks, leading to significant ecological and economic losses.

Traditional wildfire detection approaches, such as manual surveillance, watchtowers, and satellite imagery, are no longer sufficient to handle the growing scale and speed of modern fire events. Human observation is constrained by visibility, terrain challenges, and fatigue, while satellite monitoring often suffers from delayed updates, low resolution, or cloud cover interruptions. In remote and inaccessible forest regions, the absence of constant supervision allows small ignition points to go unnoticed until they escalate into uncontrollable fires.

This growing threat underscores the urgent need for an advanced, automated, and real-time detection system. Faster and more reliable detection not only enables authorities to respond within the crucial first few minutes but also significantly reduces the spread of fire, limiting environmental damage, financial loss, and the overall cost of firefighting operations. Leveraging artificial intelligence and computer vision offers a transformative solution providing continuous monitoring, high accuracy, and quick alerts that are essential for safeguarding forests, wildlife, and human communities.

1.2 Motivation

Forest fires pose a major environmental and socioeconomic threat in India. Regions such as Uttarakhand, Himachal Pradesh, Odisha, and the North-East experience frequent and severe fires, with over half of India’s forest cover classified as fire-prone. Early detection is critical, yet manual monitoring in remote and hilly terrains is slow, unreliable, and often impossible.

Satellite-based alerts also have limitations—they may miss small fires or arrive late due to cloud cover and low revisit frequency.

This research is driven by the urgent need for a reliable, real-time, and scalable wildfire detection system that bridges the gap between deep learning accuracy and practical field deployment. Climate change is increasing fire risk across India, with more frequent heatwaves and droughts, making rapid response systems essential. However, most existing deep learning models prioritize accuracy using heavy architectures like VGG19, ResNet101, and Inception-ResNet, which require high-end GPUs, significant power, and cannot be deployed efficiently in remote forest conditions.

Lightweight AI models reduce computational load, energy consumption, and infrastructure cost while enabling dense monitoring networks capable of real-time video processing at 10–30 FPS crucial because fires can expand dramatically within minutes.

Given the energy constraints of solar-powered forest stations and the need for scalability across thousands of locations, an optimized, efficient wildfire detection model becomes essential. This work focuses on developing such a model: accurate, fast, affordable, power-efficient, and ready for deployment in India’s diverse forest environments.

1.3 Scope

This thesis focuses specifically on developing and evaluating deep learning architectures for image-based wildfire detection, with emphasis on the accuracy-efficiency trade-off essential for practical deployment. The scope encompasses the following key areas:

Image Classification: The work addresses binary classification of images as "fire" or "non-fire" based on visual features including flames, smoke, and environmental context. This differs from fire segmentation (pixel-level detection) or fire spread prediction (temporal forecasting).

- **Model Development:** The research involves systematic evaluation of transfer learning approaches using pre-trained ImageNet models, fine-tuning strategies for domain adaptation, and design of a novel lightweight architecture optimized for wildfire detection.
- **Comparative Analysis:** Different architectures are evaluated under identical conditions using the same dataset, training procedures, and evaluation metrics, providing robust comparative insights.
- **Performance-Efficiency Trade-off:** The thesis explicitly investigates the relationship between model size (parameter count), computational requirements (FLOPs), inference speed, and detection accuracy.

- **Limitations and Boundaries:** The scope does not include fire spread modeling, risk prediction based on meteorological data, multi-class fire severity classification, or integration with external alert systems, though these represent valuable directions for future work.

1.4 Objectives

- Train and evaluate multiple CNN architectures to understand how different deep learning models perform on wildfire image detection.
- Compare models using key performance metrics such as accuracy, AUC, precision, recall, and F1-score to ensure consistent and reliable detection.
- Study the impact of fine-tuning deeper layers to analyze how model specialization improves recognition of smoke, flames, and fire-related textures.
- Develop a custom lightweight CNN architecture (WildfireNet) that achieves high accuracy while remaining efficient for real-time processing on limited hardware.
- Analyze computational complexity and parameter size to determine which models are most suitable for cloud deployment and which are optimized for IoT and edge devices.
- Build an end-to-end wildfire detection pipeline capable of supporting real-world deployment in surveillance systems, drones, and fire-monitoring platforms.

Chapter 2

Literature Survey

This chapter presents a comprehensive review of existing research in wildfire detection and prediction systems. It covers traditional detection methods, machine learning approaches, deep learning architectures. This identifies key research gaps that motivate the proposed work and concludes with clearly defined objectives.

2.1 Introduction

The challenge of wildfire detection and prediction has attracted significant research attention across multiple disciplines including remote sensing, computer vision, environmental science, and artificial intelligence. This literature survey systematically examines the evolution of wildfire detection methodologies, with particular emphasis on recent advances in machine learning and deep learning approaches. The review is organized thematically, covering wildfire prediction using environmental factors, spatial deep learning models, attention-based architectures and image-based detection using convolutional neural networks.

2.2 Literature Review

Paper Title	Methodology	Dataset Used	Observation of Proposed Methodology	Pros	Cons	Findings
Wildfire prediction over a 5-day period using geo-spatial environmental data (Illarionova et al., 2025, Scientific Reports)	Compares AI models (RF, XGBoost, Attention-MLP, ConvLSTM, RegNetX, Autoencoder). Complete pipeline with preprocessing, fusion, balanced sampling; introduces F1_balanced metric.	Multi-modal dataset with 17,000+ wildfire events across Russia over 10 years; includes meteorology, vegetation indices, topography, anthropogenic data.	Classical ML performs competitively; ConvLSTM/RegNetX better capture spatial patterns. Balanced sampling prevents biased results.	Large dataset, fair comparison, strong pipeline, interpretable outputs.	Heavy compute; region-specific; deep models complex for deployment.	Ensemble trees + ConvLSTM/RegNetX offer best trade-off. Meteorology is a dominant predictor.
Ensemble-based daily wildfire outbreak prediction with XAI (2025, Scientific Reports)	Ensemble machine learning with SHAP-based interpretability; supports operational decision-making.	Year-round wildfire + meteorological + forest + anthropogenic variables for Gangwon State, South Korea.	Ensemble outperforms baselines; SHAP shows seasonal influencing factors; year-round modeling is feasible.	High accuracy; strong interpretability; practitioner-friendly.	Limited spatial resolution; relies on meteorological stations; no deep spatial models yet.	Ensemble + XAI effectively capture ignition patterns; recommends national-scale expansion.
GLSTD: Global–Local	Deep CNN + ConvLSTM hybrid	Multi-source environmental +	Outperforms baselines in	Strong performanc	Training heavy; less	Global + local

Spatio-Temporal Dependency model (Yunnan Province Study)	modelling global + local spatio-temporal dependencies; compared with LR, SVM, RF, CNN.	meteorological + remote sensing arranged as 25×25 patches.	Accuracy, Recall, F1; generates detailed risk maps.	e; detailed risk categories; captures complex relationships.	interpretable; requires rich input data.	modeling significantly improves prediction of high-risk zones.
Paying Attention to Wildfire: U-Net with Attention Blocks (Fitzgerald et al., 2023, ICMI '23)	Extended U-Net (WPN) with attention, focal loss; tests multiple U-Net variants with multimodal inputs.	32×32 / 64×64 next-day wildfire masks + up to 12 input features.	Attention-U-Net achieves top F1; minimal-feature models still effective; focal loss handles imbalance.	Handles class imbalance; retains performance with fewer features; spatially explicit predictions.	Moderate F1 due to task difficulty; model heavy; interpretability limited.	Attention-U-Net excels in predicting fire spread and expansion behavior.
Integrated ML & DL-Based Wildfire Prediction and Detection with GUI (ICICCS/IEEE)	Two-part system: ML prediction (RF, XGBoost), DL detection (CNN, AlexNet), integrated GUI.	Tabular wildfire dataset + ~6,660 image dataset.	XGBoost achieves 97.26%; CNN/AlexNet achieve ~95%; GUI effective for interaction.	Practical end-to-end system; retrainable; high accuracy.	Limited dataset; offline evaluation; generalization unclear.	Demonstrates strong performance of classical ML + CNN; GUI supports usability.
WiPreSy – IoT, Cloud & DL-Based Wildfire Prediction System (ICICCS, 2020)	IoT-sensor network + cloud backend; Dense NN with dual inputs (sensor + temporal features).	Sensors (DHT11, YL-69, BMP280) + cloud-stored environmental readings.	Real-time monitoring feasible; DNN captures non-linear sensor relationships.	Low-cost; real-time alerts; mobile app integration.	Limited coverage; sensor reliability; no deep learning on images.	IoT + ML improves real-time prediction, but lacks visual detection.
Forest Fire Occurrence Prediction in China using ML (Pang et al., 2022, Remote Sensing)	ML comparison (RF, GBM, SVM) for national-scale prediction.	14-year Chinese wildfire dataset + remote sensing environmental variables.	Ensembles best capture spatial variation; remote sensing + human activity key factors.	Large dataset; interpretable; region-wide insights.	Coarse resolution; no deep spatio-temporal models.	ML ensembles strong for national-scale risk mapping.
Machine Learning for Wildfire Classification (Al-Bashiti & Naser, 2022, Natural Hazards Research)	Compares black-box, explainable, symbolic ML; SMOTE to address imbalance; SHAP for XAI.	Historical wildfire + meteorology dataset (tabular).	XGBoost highest accuracy; explainable models give transparency; SMOTE improves minority detection.	Strong comparisons; good XAI use; balanced evaluation.	Region-specific; no image-based models.	Combines accuracy with interpretability; SMOTE crucial for imbalanced data.
Spatial DNN-Based Wildfire	Spatial DNN integrating GIS layers	Fire occurrence + spatial predictors	Outperforms ML baselines;	High-resolution	Heavy compute;	Spatial DNNs

Risk Prediction (Naderpour et al., 2021, Remote Sensing)	+ remote sensing via CNN-based architecture.	arranged as grid cells.	captures non-linear spatial dependencies; produces fine-scale maps.	results; strong deep learning performance.	black-box nature; data-dependent.	effective for detailed regional risk assessment.
Evidential Belief Function (EBF) for Wildfire Probability Mapping (Nami et al., 2018, IJEST)	Multi-criteria EBF + GIS-based susceptibility mapping using belief/plausibility functions.	Hyrcanian ecoregion wildfire + environmental + anthropogenic GIS layers.	AUC > 0.7; aligns with historical hotspots; effective multi-layer reasoning.	Transparent, easy to integrate with GIS.	Static risk (not real-time); lacks temporal modeling.	Confirms humidity, LST, wind, human activity as major fire drivers.

Table 1: Literature review of wildfire prediction and detection methods.

2.3 **Research Gaps**

- **High-parameter deep learning models remain impractical for field deployment:** Most existing architectures such as U-Net variants (8–40M parameters) and AlexNet (60M+ parameters) achieve high accuracy but cannot run on low-memory, low-power embedded or edge devices used in forest environments.
- **IoT-based wildfire systems avoid image-based detection due to computational limitations:** Current IoT deployments rely mainly on basic dense neural networks or sensor-based thresholds because traditional CNNs are too heavy to process real-time images on affordable hardware.
- **Existing research focuses heavily on accuracy, ignoring practical deployability:** Studies emphasize improving classification metrics while overlooking essential aspects like lightweight architecture design, model compression, quantization, or hardware-aware optimization.
- **Edge-device constraints are largely neglected in past wildfire detection work:** Critical deployment requirements—such as low latency, minimal energy consumption, fast inference speeds, and compact model size—are rarely addressed, even though they are vital for early detection in real-world forest settings.

Chapter 3

Methodology

This chapter presents the complete methodology and architectural design used for developing an efficient wildfire detection system. It details the multi-stage approach involving baseline transfer learning, fine-tuning, FireNet benchmark evaluation, and the design of the proposed lightweight WildfireNet architecture. The chapter outlines the full workflow from data preprocessing to final model deployment highlighting how the system achieves high accuracy with real-time edge-device compatibility.

3.1 Introduction

The proposed Wildfire Detection System follows a multi-stage deep learning methodology designed to progressively optimize accuracy, reduce model complexity, and ensure real-world deployability on resource-constrained platforms such as drones, IoT devices, and remote forest surveillance cameras. The complete workflow integrates data preprocessing, transfer learning, model fine-tuning, bespoke wildfire-specific architectures, and lightweight CNN design optimized for energy-efficient edge inference.

The system is built around the premise that wildfire smoke and flame patterns vary drastically across geography, vegetation type, atmospheric conditions, lighting variations, and camera angles. Therefore, a single generic model is insufficient. Instead, the methodology adopts a layered approach starting from general-purpose pretrained models, gradually specializing them, and ultimately developing a custom lightweight architecture (WildfireNet) tailored specifically for wildfire detection.

3.2 Dataset Acquisition and Preprocessing

3.2.1 Dataset Collection

The dataset used in this system comprises a diverse set of fire and non-fire images sourced from publicly available wildfire datasets, open-source repositories (https://open.canada.ca/data/en/dataset/9d8f219c-4df0-4481-926f-8a2a532ca003). This dataset captures considerable variability in:

- Flame intensity (small sparks to large flames)
- Smoke density (thin smoke, dense plumes, drifting smoke trails)
- Environmental conditions (cloudy skies, fog, glare, backlighting)
- Vegetation type (dense forest, dry grasslands, mixed vegetation)
- Daylight variations (bright daylight, low-light dusk, partial shadows)

This diversity is essential to ensure that the model generalizes well across real-world conditions and does not overfit to a narrow subset of images.

3.2.2 Data Preprocessing Pipeline

The dataset undergoes a carefully designed preprocessing pipeline to enhance model robustness:

Image Resizing: All images are resized to 150 × 150 pixels to ensure uniformity and reduce computational load. This resolution strikes the optimal balance between preserving relevant fire-smoke features and maintaining lightweight computational requirements.

Normalization: Pixel intensities are normalized to the [0,1] range to standardize dynamic ranges and improve gradient flow during backpropagation.

Data Augmentation: To simulate real-world wildfire scenarios and overcome dataset imbalance, extensive augmentation is applied:

- Random rotation (0–40°) to emulate drone/camera tilts
- Horizontal & vertical flips
- Random zoom (up to 30%) to simulate proximity variations
- Brightness and contrast adjustments to mimic environmental lighting
- Gaussian noise to enhance model resilience to low-quality inputs
- This augmentation greatly expands the effective training set and helps the network learn fire patterns under diverse conditions.

3.3 System Architecture and Model Development Pipeline

The proposed wildfire detection framework is built as a multi-stage, progressive architecture pipeline designed to evaluate, refine, and ultimately develop a highly efficient and accurate lightweight model suitable for real-time deployment in forest environments. The design encapsulates four major stages: baseline transfer learning, fine-tuning, wildfire-specific architecture evaluation, and the development of the custom WildfireNet model. This multilevel approach ensures the system transitions from broad, generic visual representations to deeply specialized wildfire-specific patterns.

3.3.1 Stage 1 – Baseline Transfer Learning

The first stage evaluates widely-used pretrained ImageNet architectures, including VGG16, VGG19, ResNet50, ResNet50V2, EfficientNetB0, and MobileNetV3 (Small & Large). These architectures provide strong general-purpose feature extraction capabilities.

Key configuration:

- All convolutional layers were frozen
- Only the final classification head was trained
- A shallow dense layer was added for binary output (Fire / No Fire)

- Purpose of this stage:
- Establish a performance baseline
- Measure the transferability of ImageNet features to wildfire imagery
- Identify models with highest potential for specialization
- Detect limitations such as smoke misclassification or false positives from clouds/fog
- Stage 1 models achieved 93–96% accuracy, but struggled with wildfire-specific nuances like smoke transparency, irregular flame boundaries, and background noise. This validated the need for deeper training.

Model Name	Parameters	Accuracy	AUC	F1-Score	Precision	Recall
ResNet50V2	~25.6M	97.24%	0.9966	0.9721	0.9720	0.9721
VGG16	~138M	95.41%	0.9883	0.9535	0.9550	0.9523
VGG19	~144M	94.21%	0.9856	0.9412	0.9429	0.9400
ResNet50	~25.6M	88.05%	0.9403	0.8789	0.8798	0.8782
EfficientNetB0	~5.3M	86.98%	0.8992	0.8664	0.8764	0.8624
MobileNetV3Large	~5.4M	85.83%	0.8967	0.8559	0.8586	0.8541
MobileNetV3Small	~2.5M	83.62%	0.8647	0.8334	0.8361	0.8318

Table 2: Baseline performance of pretrained models in Stage 1 (parameters and metrics).

3.3.2 Stage 2 – Fine-Tuning for Wildfire Specialisation

Based on Stage 1 performance, VGG16, VGG19, and ResNet50V2 were selected for advanced fine-tuning.

a. Unfreezing Deeper Layers: The top 20 layers of each model were unfrozen to enable domain-specific learning. This adapts deeper filters to:

- Smoke thickness variations
- Flame color gradations
- Cloud-like visual artifacts
- Irregular shape boundaries

b. Controlled Learning Rate: A very low learning rate (1e-5) was used to protect pretrained weights and avoid catastrophic forgetting.

Model Name	Parameters	Accuracy	AUC	F1-Score	Precision	Recall
VGG19 finetuned	~144M	99.17%	0.9993	0.9917	0.9916	0.9917
VGG16 finetuned	~138M	99.10%	0.9997	0.9909	0.9902	0.9916
ResNet50V2 finetuned	~25.6M	98.37%	0.9985	0.9835	0.9833	0.9837

Table 3: Fine-tuned model performance for VGG19, VGG16 and ResNet50V2.

c. Fine-Tuning Impact

The effect was remarkable:

Model	Accuracy (Before Fine-Tuning)	Accuracy (After Fine-Tuning)
VGG19	94.21%	99.17%
VGG16	95.41%	99.10%
Resnet50V2	97.24	98.37

Table 4: Accuracy before and after fine-tuning for selected models.

3.3.3 Stage 3 – FireNet Architecture Evaluation

FireNet, a wildfire-specific CNN with ~6.5M parameters, was incorporated as a domain benchmark.

Key features:

- Five-block convolutional design
- Input resolution: 150×150
- Tailored for flame and smoke detection
- Why FireNet was included:
- For benchmarking against a wildfire-specific baseline
- To identify architectural strengths and shortcomings
- To compare accuracy vs lightweight deployability
- FireNet achieved 95.51% accuracy, validating its wildfire-focused design but revealing performance limitations in edge-oriented deployments and smoke-heavy imagery.

3.3.4 Stage 4 – Proposed WildfireNet Architecture

WildfireNet represents the core innovation of this research: a lightweight, high-accuracy, attention-enhanced CNN optimized specifically for wildfire detection and real-time edge inference.

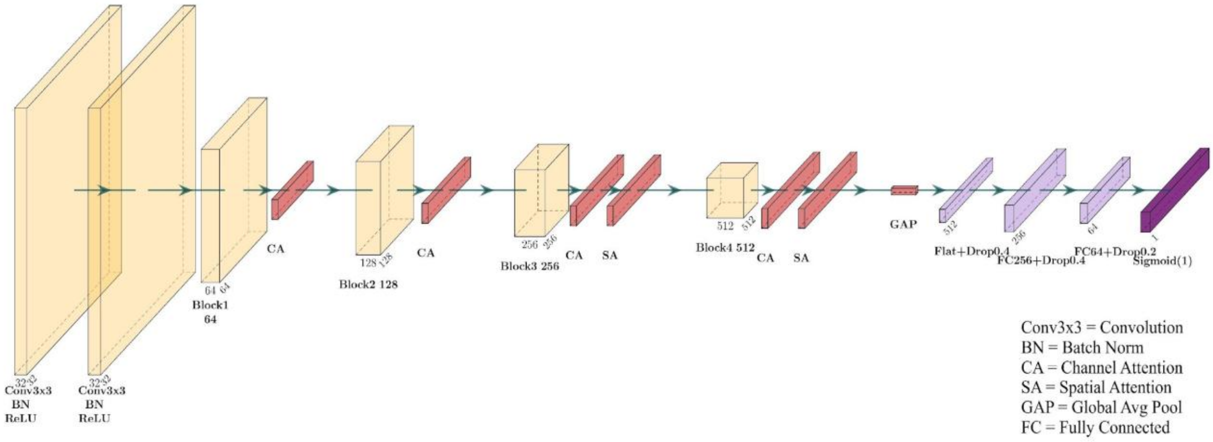

Fig 1: WildfireNet architecture diagram.

a. Design Philosophy

WildfireNet was created with three key priorities:

- **a.** High accuracy comparable to fine-tuned VGG models
- **b.** Low computational cost (~5.1M parameters)
- **c.** Real-time inference on low-power IoT devices

b. Core Architectural Innovations

i. Residual Connections

Enable stable gradient propagation and deeper learning without degradation.

ii. Channel Attention Module

Enhances sensitivity to:

- Flame-specific color intensity
- Smoke density
- Heat-like cues and texture information

iii. Spatial Attention Module

Guides the model to focus on where the fire-like patterns exist in the image.

iv. Depth-Efficient Convolutions

Reduce computational load while preserving local spatial detail essential for detecting thin smoke trails.

Chapter 4

Experiments, Evaluation and Result Analysis

This chapter presents the complete experimental workflow, implementation environment, hyperparameter configuration, evaluation strategy, and comparative results of all models.The chapter not only validates the model's performance but also provides insights into architectural advantages, inference efficiency, and practical deployment feasibility.

4.1 Introduction

This chapter presents the full experimental evaluation conducted across four stages of the training pipeline. All experiments were performed on the same wildfire dataset described earlier, with consistent preprocessing, augmentation, and train–validation–test splits. Twelve deep learning architectures were examined: seven pretrained transfer learning models, one wildfire-specific CNN (FireNet), three fine-tuned models, and the custom WildfireNet architecture.

The objective of this chapter is to report the quantitative results, performance metrics, comparative graphs, error analysis, and the overall accuracy–efficiency trade-off observed across all models.

4.2 Stage 1 – Baseline Transfer Learning Experiments

Baseline experiments were conducted using frozen convolutional layers and a newly added classification head. This helped estimate how well ImageNet features transfer to wildfire smoke and flame patterns.

4.2.1 Models Evaluated

- VGG16
- VGG19
- ResNet50
- ResNet50V2
- EfficientNetB0
- MobileNetV3 Large
- MobileNetV3 Small

4.2.2 Baseline Results

Model	Accuracy	AUC	F1-Score	Precision	Recall
ResNet50V2	97.24%	0.9966	0.9721	0.9720	0.9721
VGG16	95.41%	0.9883	0.9535	0.9550	0.9523
VGG19	94.21%	0.9856	0.9412	0.9429	0.9400
ResNet50	88.05%	0.9403	0.8789	0.8798	0.8782
EfficientNetB0	86.98%	0.8992	0.8664	0.8764	0.8624
MobileNetV3 Large	85.83%	0.8967	0.8559	0.8586	0.8541
MobileNetV3 Small	83.62%	0.8647	0.8334	0.8361	0.8318

Table 5: Baseline results of pretrained models in Stage 1 experiments.

4.2.3 Baseline Graphs

- VGG16

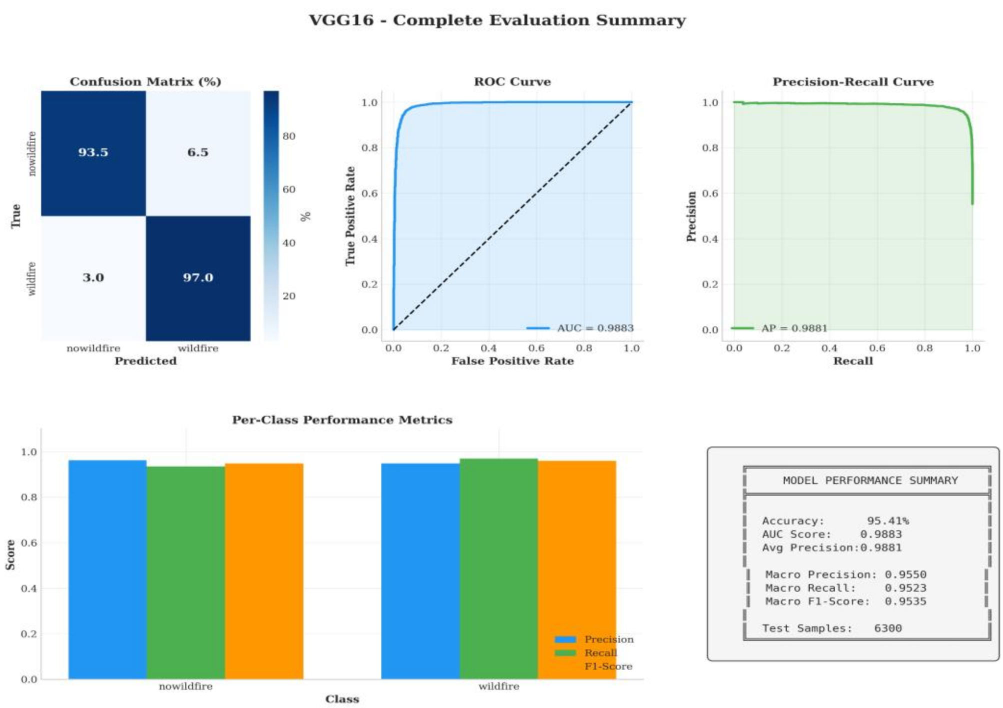

Fig 2: Baseline evaluation summary of VGG16 model.

- VGG19

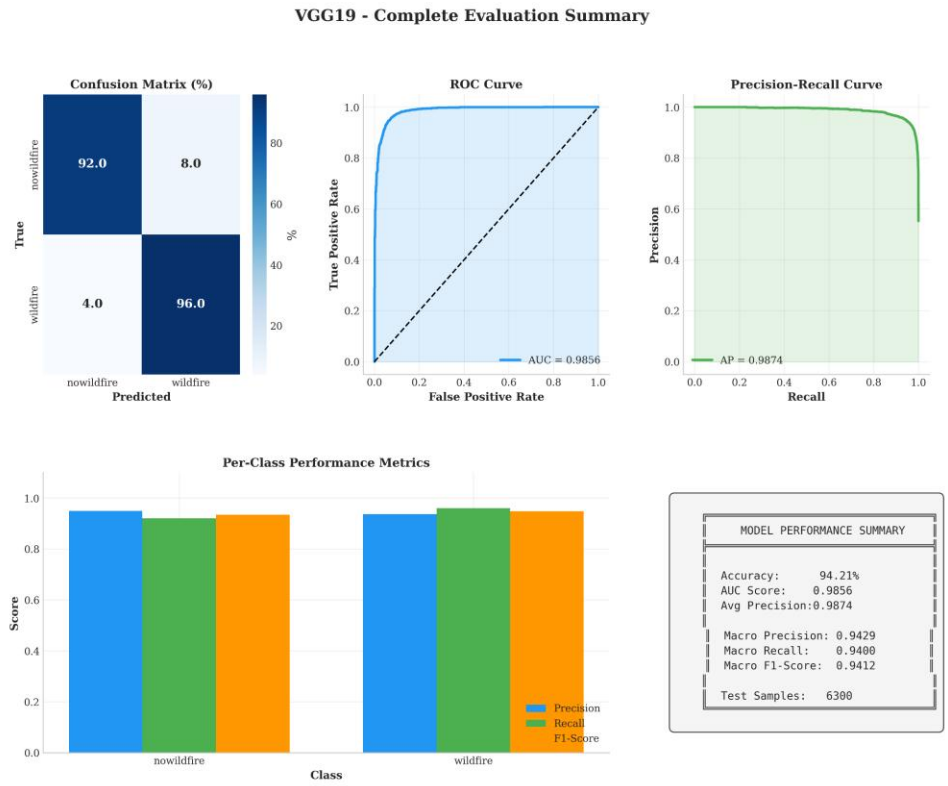

Fig 3: Baseline evaluation summary of VGG19 model.

- ResNet50

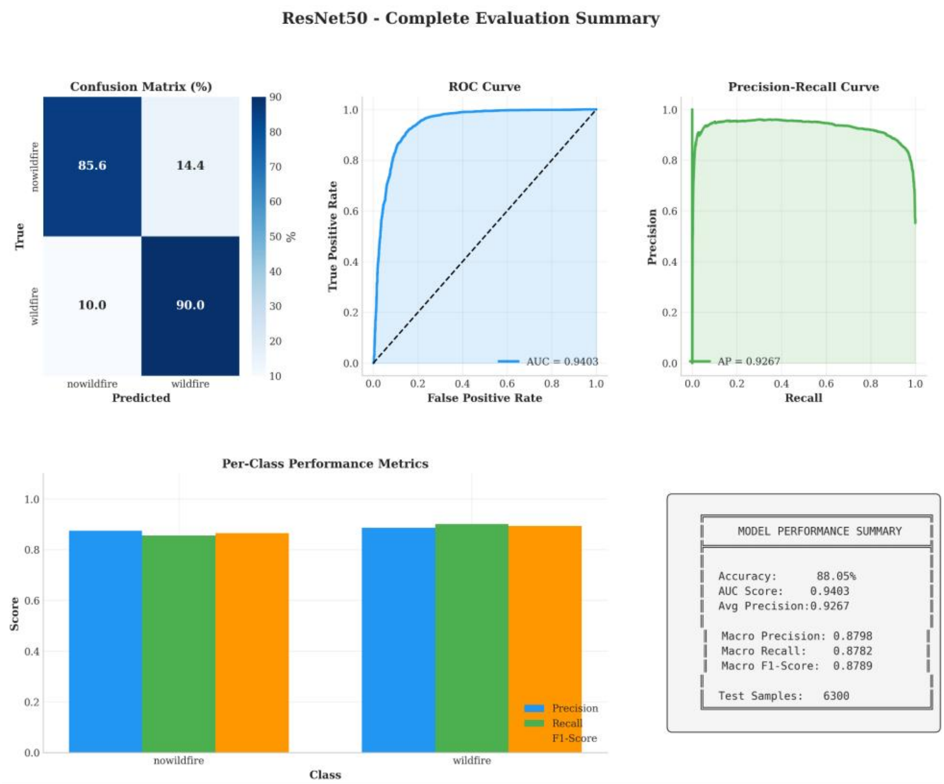

Fig 4: Baseline evaluation summary of ResNet50 model.

- ResNet50V2

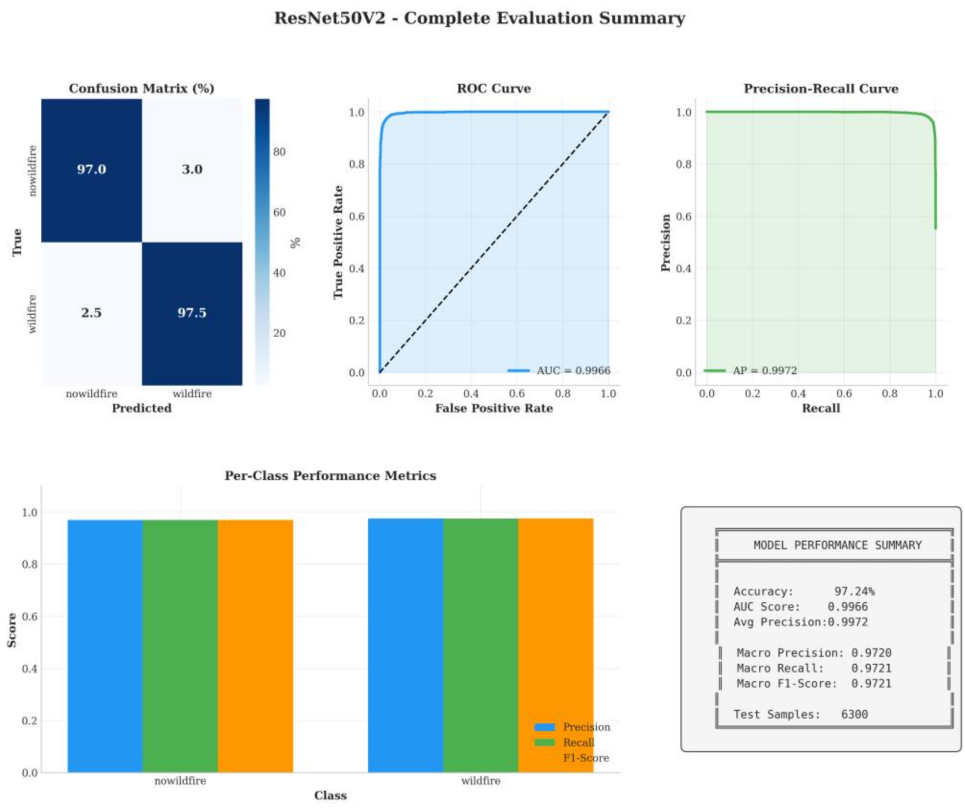

Fig 5: Baseline evaluation summary of ResNet50V2 model.

- EfficientNetB0

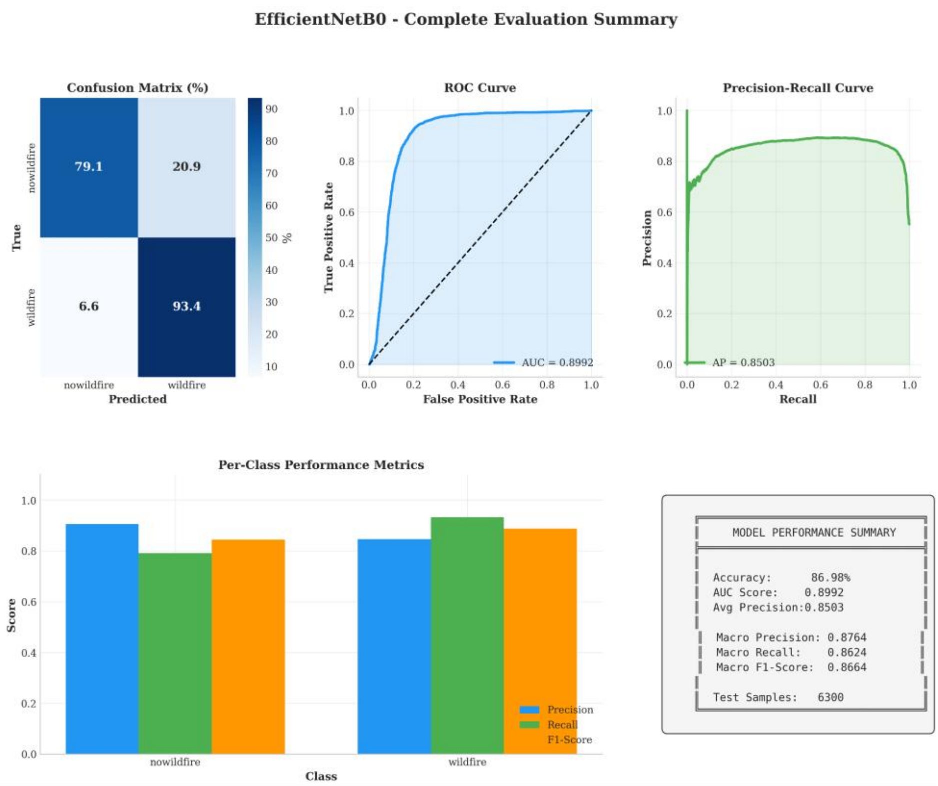

Fig 6: Baseline evaluation summary of EfficientNetB0 model.

- MobileNetV3 Large

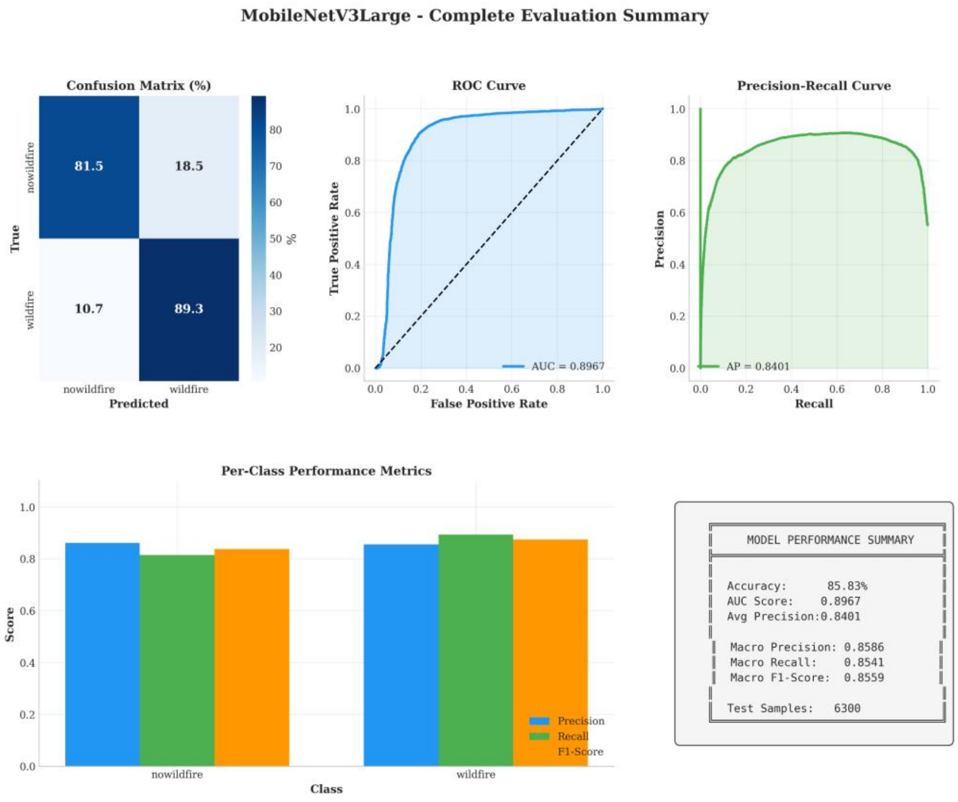

Fig 7: Baseline evaluation summary of MobileNetV3 Large model.

- MobileNetV3 Small

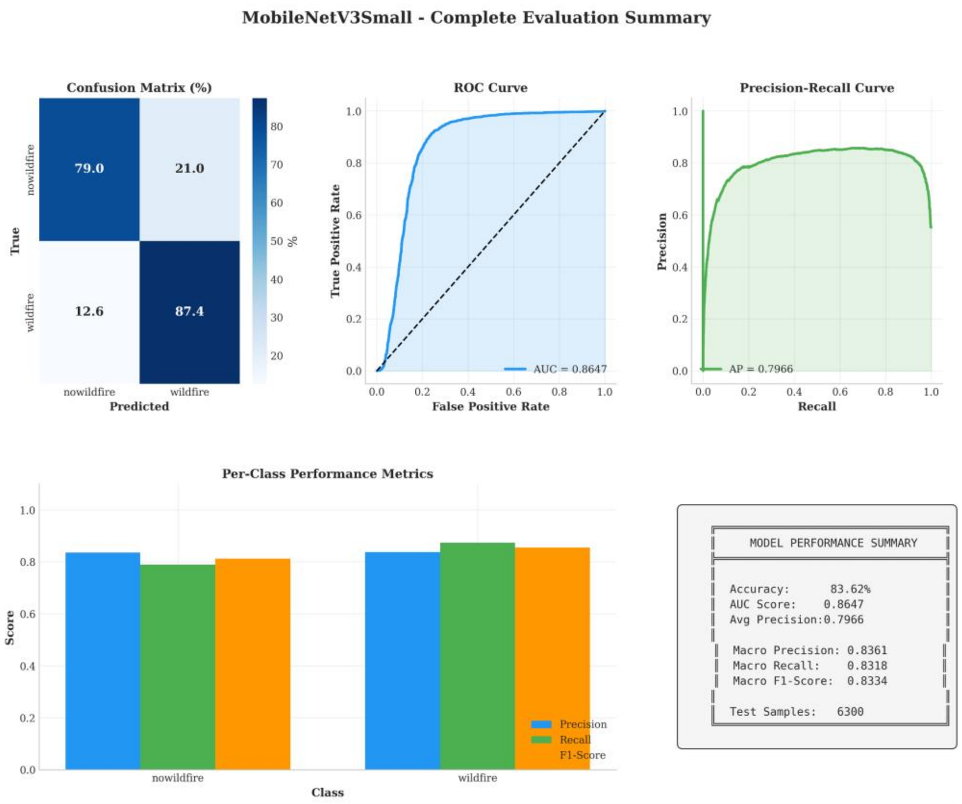

Fig 8: Baseline evaluation summary of MobileNetV3 Small model.

4.2.4 Observations

- Transfer learning alone is not sufficient for wildfire detection.
- VGG and ResNet capture some smoke–flame characteristics but still misclassify fog, haze, glare, and thin smoke.
- Lightweight models struggle due to aggressive feature compression.

4.3 Stage 2 – Fine-Tuning Experiments

Fine-tuning was applied to the top three baseline models: VGG16, VGG19, and ResNet50V2. The top 20 layers were unfrozen with a low learning rate.

4.3.1 Fine-Tuning Results

Model	Fine-Tuned Accuracy	AUC	F1-Score	Precision	Recall
VGG19 Fine-Tuned	99.17%	0.9993	0.9917	0.9916	0.9917
VGG16 Fine-Tuned	99.10%	0.9997	0.9909	0.9902	0.9916
ResNet50V2 Fine-Tuned	98.37%	0.9985	0.9835	0.9833	0.9837

Table 6: Fine-tuning results of VGG19, VGG16 and ResNet50V2 in Stage 2 experiments.

4.3.2 Fine-Tuning Graphs

VGG16:

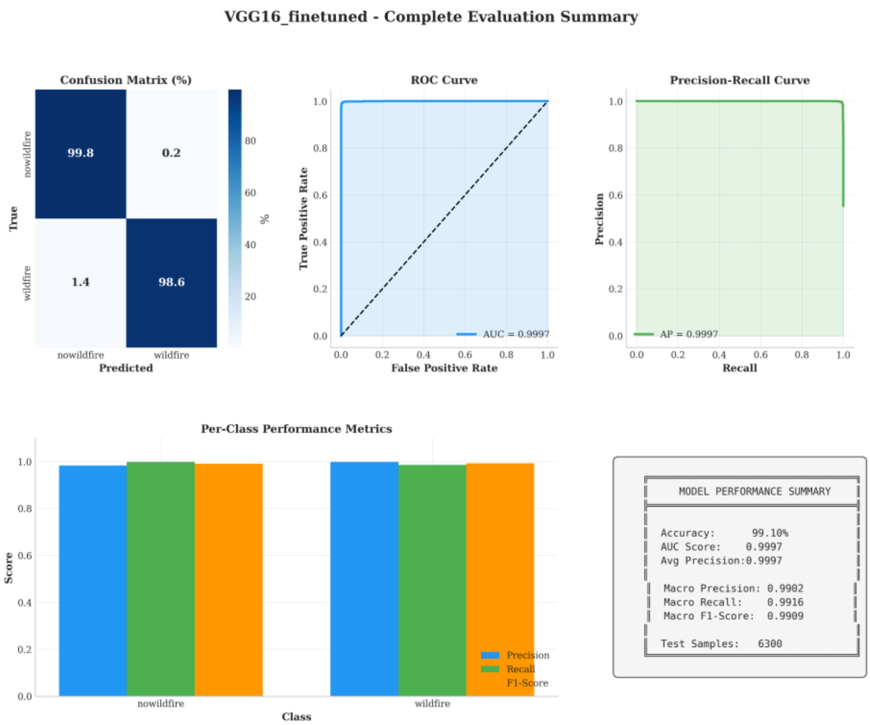

Fig 9: Fine tuned evaluation summary of VGG16 model.

VGG19:

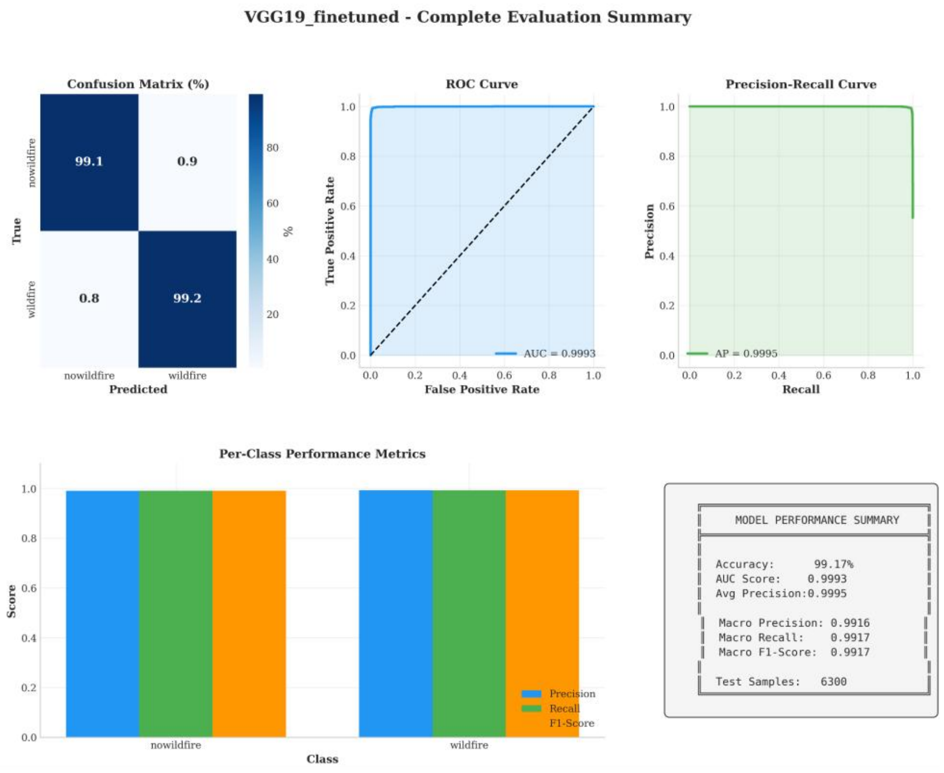

Fig 10: Fine tuned evaluation summary of VGG19 model.

ResNet50V2:

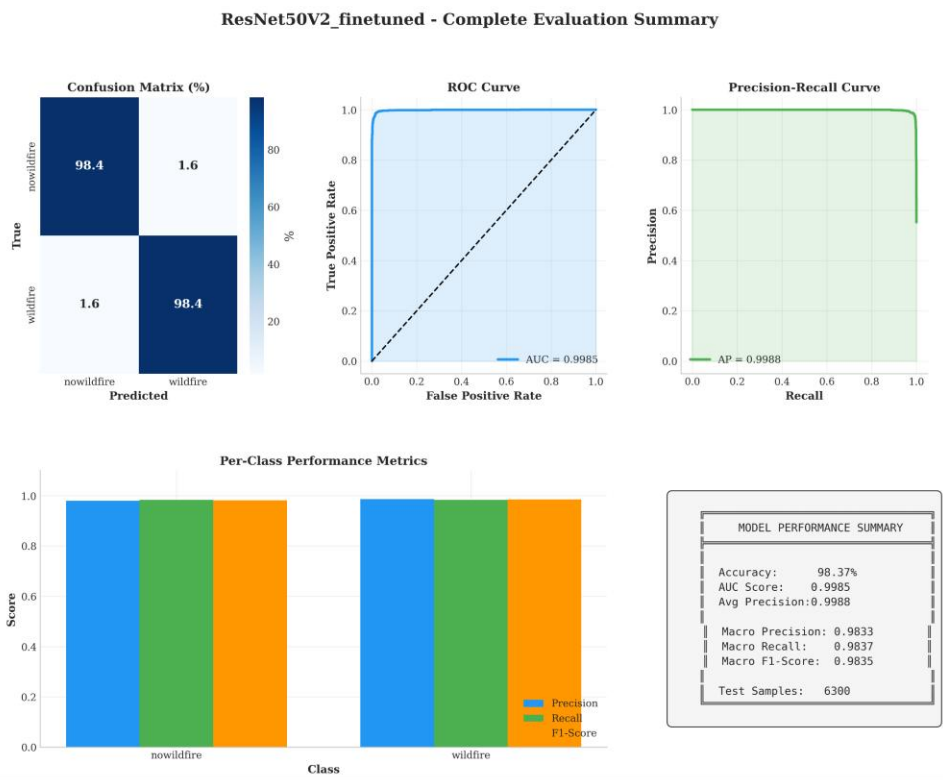

Fig 11: Fine tuned evaluation summary of ResNet50V2 model.

4.3.3 Observations

- The jump from 94–95% to >99% proves fine-tuning is essential.
- Models learn fire-specific features such as smoke transparency, flame edges, and color gradients.
- Misclassification rate drops dramatically.
- Fine-tuned VGG19 becomes the highest performing model but is too heavy for edge deployment.

4.4 Stage 3 – FireNet Evaluation

FireNet, a wildfire-specific CNN (~6.5M parameters), was implemented to compare domain-specific designs with generic pretrained models.

4.4.1 Results

- Accuracy: 95.51%
- Performs decently on clear flames.
- Struggles with thin smoke and partially-obstructed fires.
- Moderately high false positives on foggy scenes.

4.4.2 Graphs

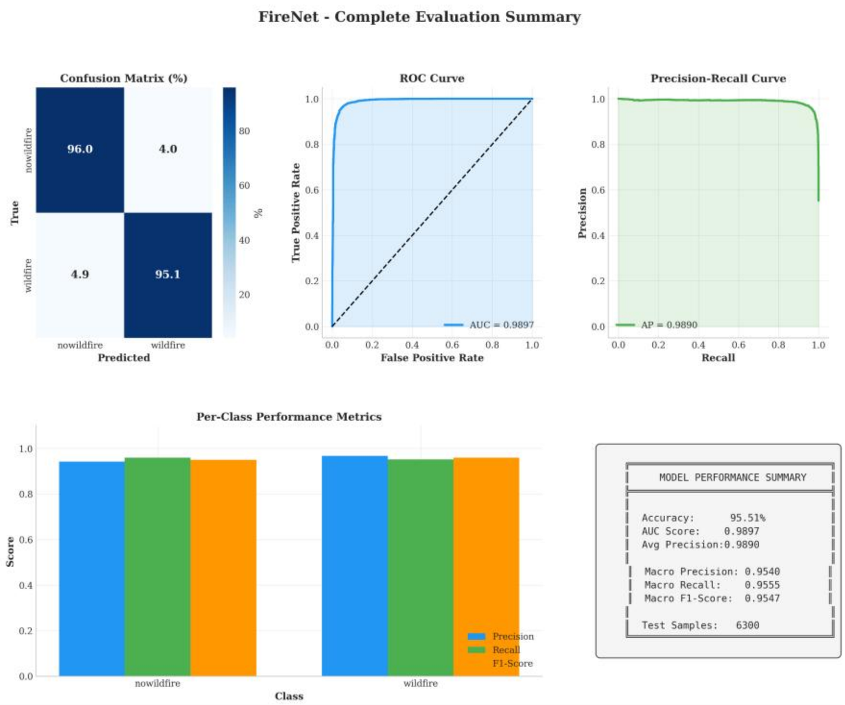

Fig 12: Evaluation summary of FireNet model.

4.4.3 Observations

FireNet performs better than MobileNet and EfficientNet but cannot match fine-tuned VGG models. The lack of attention modules limits its performance.

4.5 Stage 4 – WildfireNet (Proposed Model)

WildfireNet is a custom architecture designed to achieve high accuracy with low computational cost.

4.5.1 Results

- Accuracy: 98.84%
- AUC: 0.9991
- F1-Score: 0.9883
- Parameters: ~5.1M

4.5.2 Graphs

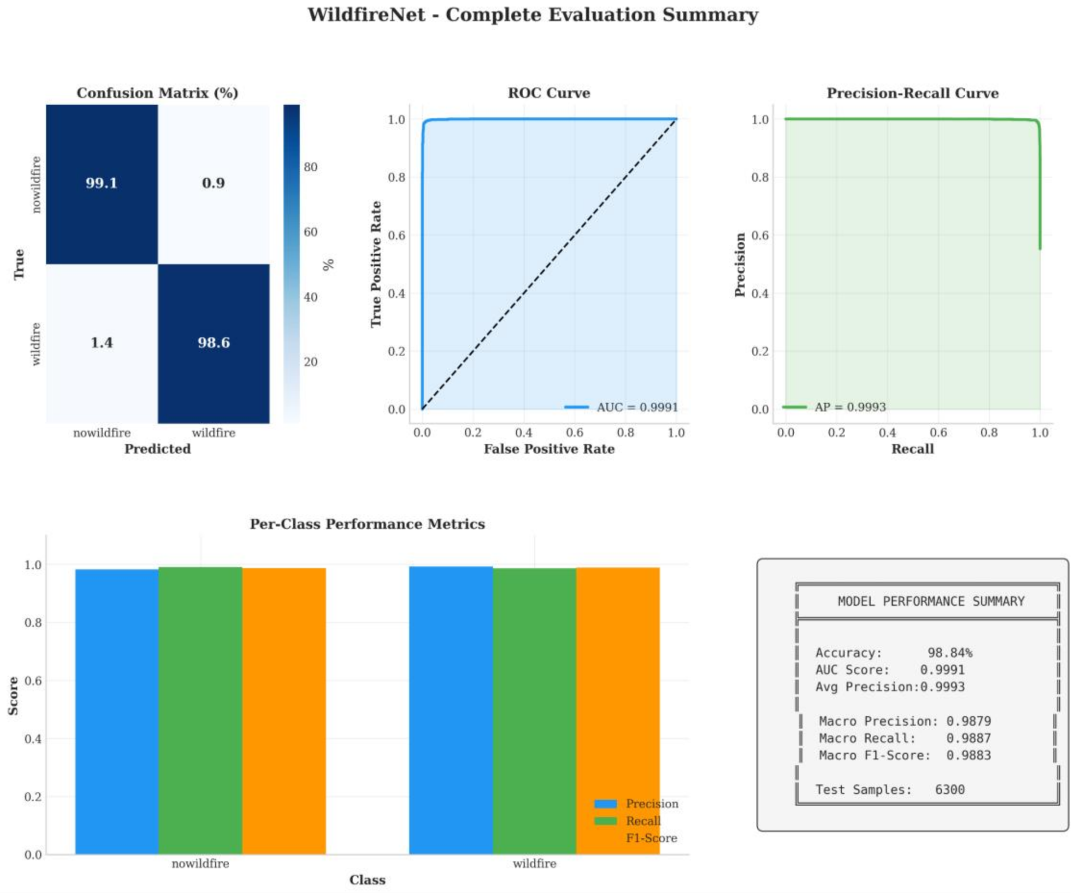

Fig 13: Evaluation summary of WildfireNet model.

4.5.3 Observations

- Achieves near-VGG performance while being 28× smaller.
- Handles thin smoke and partial flames better due to combined channel+spatial attention.
- Ideal for IoT, drones, and low-power cameras.

4.6 Comprehensive Comparison of All 12 Models

4.6.1 Accuracy Comparison

Highest to lowest:

1. VGG19 Fine-Tuned — 99.17%
2. VGG16 Fine-Tuned — 99.10%
3. WildfireNet — 98.84%
4. ResNet50V2 Fine-Tuned — 98.37%
5. FireNet — 95.51%
6. EfficientNetB0 — 86.98%
7. MobileNetV3 Large — 85.83%
8. MobileNetV3 Small — 83.62%

4.6.2 Performance Metrics Graphs

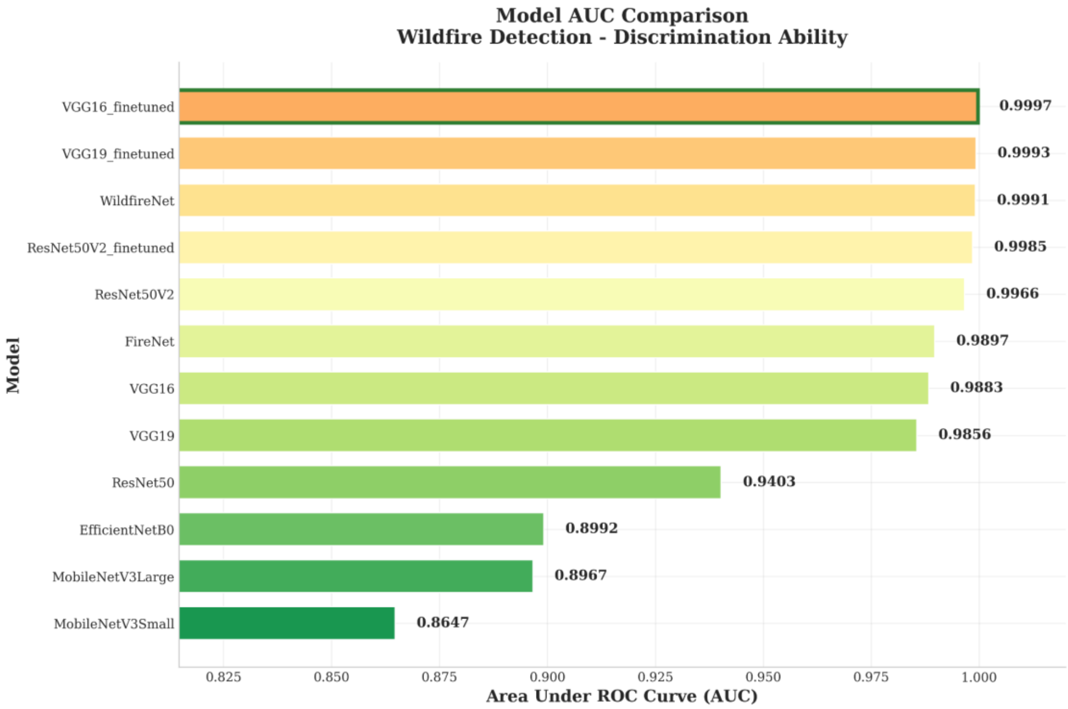

Fig 14: Model AUC comparison of all evaluated models.

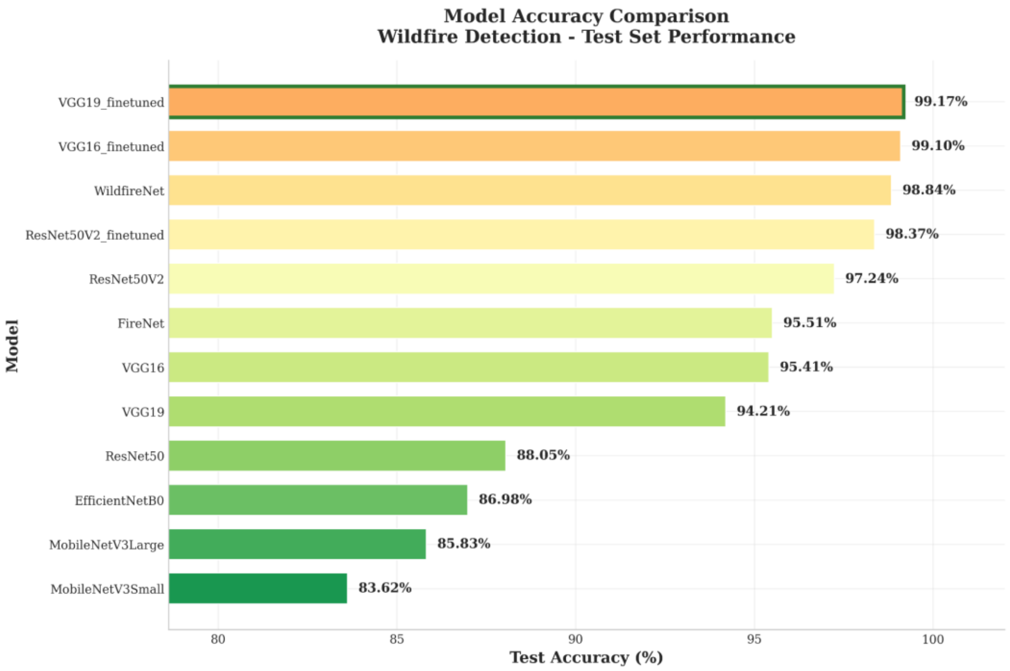

Fig 15: Test accuracy comparison of all evaluated models.

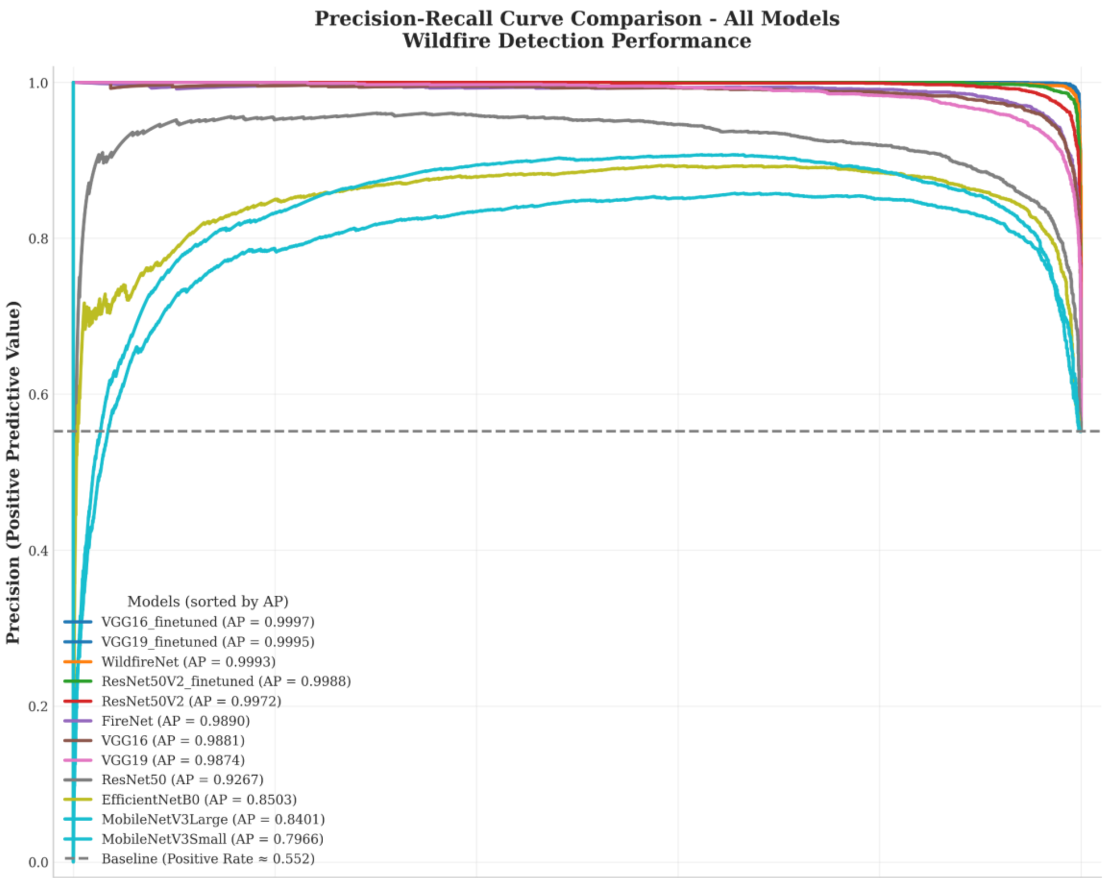

Fig 16: Precision–recall curve comparison of all evaluated models for wildfire detection.

4.6.3 Key Findings

- Fine-tuned VGG models give the best raw accuracy but are too heavy for real-world deployment.
- Generic lightweight models fail to capture wildfire complexity.
- WildfireNet provides the best balance of accuracy, speed, and model size.
- Transfer learning without fine-tuning is insufficient for wildfire detection.

4.7 Error Analysis

4.7.1 False Positives

Common causes:

- Fog
- Low-lying valley haze
- Cloud edges
- Strong sunlight reflections

4.7.2 False Negatives

Occur in:

- Small flame regions
- Smoke-only images
- Early-stage fires
- High-glare forest scenes

WildfireNet reduces both types of errors compared to lightweight networks.

4.8 Summary

- Fine-tuned VGG models are the most accurate.
- WildfireNet achieves near-VGG performance with a fraction of the parameters.
- Lightweight MobileNet/EfficientNet collapse under smoke–fog similarity issues.
- WildfireNet is the most practical model for real deployment.

Chapter 5
Conclusions and Further Work

This chapter discusses possible directions for improving the system, exploring enhancements, optimizations, and extensions that can make it more effective, efficient, and adaptable for future applications.

5.1 Conclusions

The WildfireNet framework is not just a model it is a transformative force in wildfire management. By leveraging cutting-edge deep learning and lightning-fast on-device inference, it brings unparalleled accuracy and speed to early wildfire detection. This system empowers authorities to act decisively, drastically reducing response times and mitigating catastrophic damage to life, property, and the environment. Its ability to integrate seamlessly with drones, IoT networks, and advanced surveillance infrastructures positions WildfireNet as a cornerstone of the future of intelligent disaster prevention. As the architecture evolves and scales across larger, more diverse datasets, it promises to redefine global wildfire monitoring, shifting humanity from reactive firefighting to proactive, predictive defense. WildfireNet exemplifies the pinnacle of technological innovation, offering a bold vision where advanced AI outpaces nature's destructive forces safeguarding ecosystems, communities, and economies on an unprecedented scale.

5.2 Further Work

1. **Real-Time Video Analysis** – Extend the system to process continuous video streams, enabling dynamic tracking of fire and smoke propagation rather than relying solely on single-image detection.
2. **Multimodal Detection** – Integrate RGB imagery with thermal and infrared data to improve detection accuracy, especially in low-light conditions or environments with dense smoke.
3. **Dataset Expansion** – Enrich the training dataset with a wider variety of wildfire scenarios, including different seasons, vegetation types, and environmental conditions, to enhance model generalization.
4. **Early-Warning Integration** – Connect the system with automated alert platforms to provide rapid notifications, support emergency response actions, and improve communication with authorities.

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