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НАУЧНО-ИССЛЕДОВАТЕЛЬСКИЙ ЖУРНАЛ МЕНЕДЖМЕНТА И ЭКОНОМИКИ

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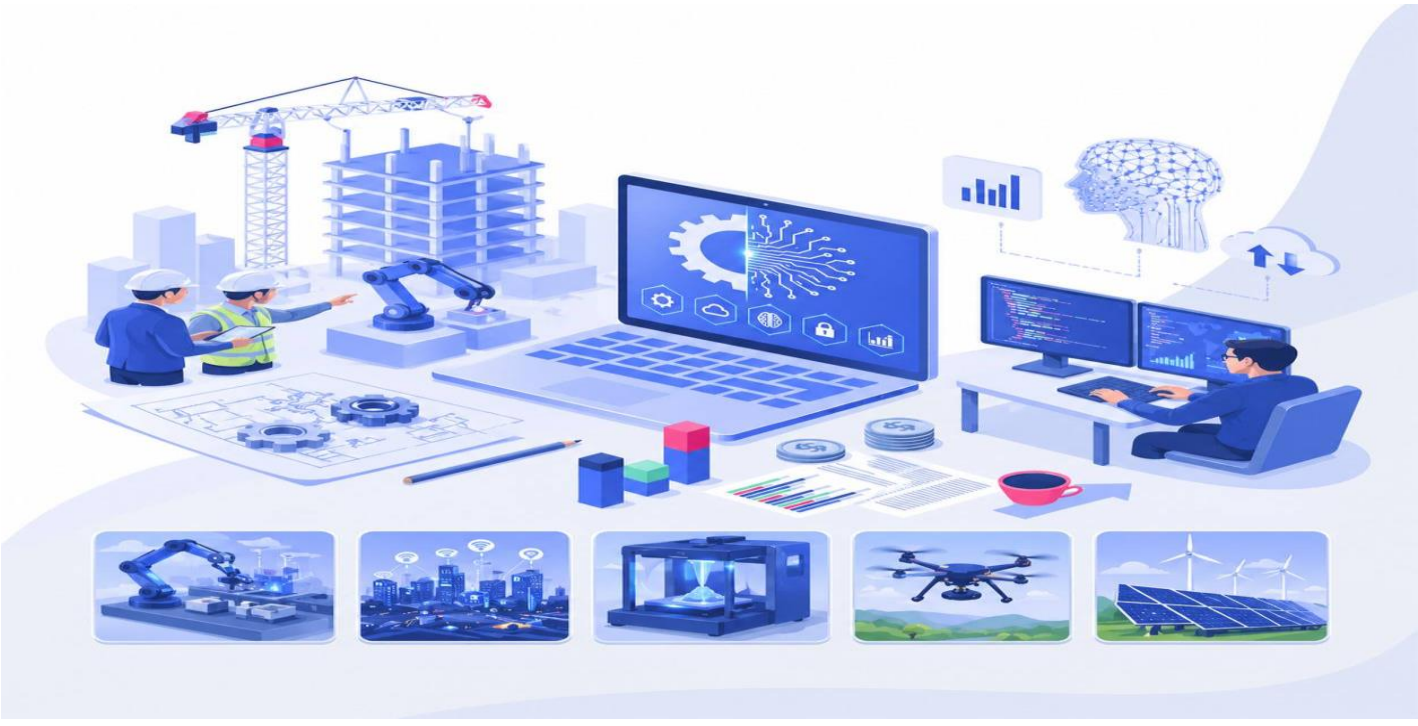

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21 MAY 2026 YIL

МИНИСТЕРСТВО ВЫСШЕГО ОБРАЗОВАНИЯ, НАУКИ И ИННОВАЦИЙ РЕСПУБЛИКИ УЗБЕКИСТАН

ТАШКЕНТСКИЙ ИНСТИТУТ УПРАВЛЕНИЯ И ЭКОНОМИКИ

МЕЖДУНАРОДНАЯ НАУЧНО-ПРАКТИЧЕСКАЯ КОНФЕРЕНЦИЯ НА ТЕМУ «ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ И ЦИФРОВЫЕ ИННОВАЦИОННЫЕ ТЕХНОЛОГИИ В ИНЖЕНЕРИИ: СОВРЕМЕННЫЕ РЕШЕНИЯ И ПЕРСПЕКТИВЫ»

21 МАЯ 2026 ГОДА

MINISTRY OF HIGHER EDUCATION, SCIENCE AND INNOVATIONS OF THE REPUBLIC OF UZBEKISTAN

TASHKENT INSTITUTE OF MANAGEMENT AND ECONOMICS

INTERNATIONAL SCIENTIFIC AND PRACTICAL CONFERENCE ON THE THEME "ARTIFICIAL INTELLIGENCE AND DIGITAL INNOVATIVE TECHNOLOGIES IN ENGINEERING: MODERN SOLUTIONS AND PROSPECTS" 21 MAY 2026

“Muhandislikda sun’iy intellekt va raqamli innovatsion texnologiyalar: zamonaviy yechimlar va istiqbollar” Xalqaro ilmiy-amaliy anjuman tezislar to‘plami. 2026-yil 21-may.

Ushbu to‘plamda — “Muhandislikda sun’iy intellekt va raqamli innovatsion texnologiyalar: zamonaviy yechimlar va istiqbollar” Xalqaro ilmiy –amaliy anjuman ishtirokchilarining tezislari keltirilgan. Anjuman kun tartibiga kiritilgan masalalar dolzarb bo‘lib, u yalpi ma‘ruzalar va amaliy zamonaviy muhandislik ta’limida raqamli transformatsiya va sun’iy intellekt, muhandislik yechimlari va sanoat 4.0, robototexnika va avtomatlashtirilgan boshqaruv tizimlari, kiberxavfsizlik va ma'lumotlarni himoya qilish, ta’limda axborot va innovatsion texnologiyalarning qo‘llanilishi, biznes jarayonlar va raqamli iqtisodiyotga axborot texnologiyalarining o‘rni kabi sho‘balardan tashkil topgan. To‘plam sohasi mutaxassislari, ilmiy tadqiqotchilar, professor-o‘qituvchilar, doktorantlar, magistrlar va talabalar uchun mo‘ljallangan.

Maqolalarda keltirilgan ma‘lumotlarning haqqoniyligi uchun mualliflar mas‘uldir.

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Tahririyat jamoasi

TOWARDS TRUSTWORTHY WILDFIRE DETECTION: INTEGRATING EXPLAINABILITY AND UNCERTAINTY IN DEEP LEARNING MODELS

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Abstract. Wildfires are now a climate-driven, year-round hazard, raising the value of deep learning for early visual detection. This study presents BlazeVeritas AI, a wildfire detection framework integrating CNN, ResNet-18 [8], and DenseNet-121 [5] with Grad-CAM [7] explainability and uncertainty calibration via Monte Carlo Dropout [9] and Temperature Scaling, deployed through FastAPI and Streamlit. Results show that pairing explanation with calibrated uncertainty improves the reliability of wildfire decision-support systems.

Keywords: *trustworthy artificial intelligence; wildfire detection; Grad-CAM; uncertainty calibration; deep learning.*

Аннотация. Лесные пожары стали круглогодичной, усиливаемой климатом угрозой, что повышает роль глубокого обучения для их раннего визуального обнаружения. В статье представлена система BlazeVeritas AI, объединяющая CNN, ResNet-18 и DenseNet-121 с объяснимостью Grad-CAM и оценкой неопределённости на основе Monte Carlo Dropout и Temperature Scaling, реализованная средствами FastAPI и Streamlit. Результаты показывают, что совместное применение объяснимости и калиброванной неопределённости повышает надёжность систем поддержки принятия решений.

Ключевые слова: *доверенный искусственный интеллект; обнаружение лесных пожаров; Grad-CAM; калибровка неопределённости; глубокое обучение.*

Annotatsiya. Yong‘inlar iqlim o‘zgarishi ta’sirida yil davomida davom etadigan tahdidga aylangan bo‘lib, bu ularni erta aniqlashda chuqur o‘rganishning ahamiyatini oshiradi. Maqolada CNN, ResNet-18 va DenseNet-121 modellarini Grad-CAM tushuntirish mexanizmi hamda Monte Carlo Dropout va Temperature Scaling asosidagi noaniqlik bahosi bilan birlashtiruvchi BlazeVeritas AI tizimi taqdim etiladi. Tizim FastAPI va Streamlit yordamida ishlab chiqilgan. Natijalar tushuntiruvchanlik va noaniqlikni birga qo‘llash qaror qabul qilish ishonchliligini oshirishini ko‘rsatadi.

Kalit so‘zlar: ishonchli sun’iy intellekt; yong‘inni aniqlash; Grad-CAM; noaniqlikni kalibrlash; chuqur o‘rganish.

1. Introduction

Wildfires have shifted from seasonal hazards into year-round, climate-driven emergencies that routinely overwhelm conventional surveillance watch towers, slow satellites, and citizen reports. Computer vision over fixed cameras, drones, and edge sensors narrows that gap, flagging ignitions in seconds rather than minutes [1], and modern CNNs now rival human reviewers on benchmark accuracy [2]. Yet accuracy is a weak proxy for operational readiness: deep models behave as black boxes and are systematically overconfident, often claiming 99% certainty on inputs they get right only 80% of the time [3]. Where false alarms erode vigilance and missed detections cost lives, that pairing is corrosive.

This study therefore asks not how to raise accuracy but under what conditions a wildfire classifier can be trusted. Trust is treated as the conjunction of two signals — explainability through Grad-CAM, which reveals where the model looked, and uncertainty through Monte Carlo (MC) Dropout with Temperature Scaling, which indicates how far the output can be believed. The contributions are threefold: (i) BlazeVeritas AI, an end-to-end FastAPI/Streamlit pipeline returning prediction, explanation, and calibrated uncertainty as one payload; (ii) a benchmark of a custom CNN, ResNet-18, and DenseNet-121 on accuracy, Expected Calibration Error (ECE), and explanation–evidence alignment; and (iii) a decision-support framing in which uncertainty thresholds route ambiguous inputs to human review.

2. Literature Review

Vision-based fire detection has passed through three waves. Early systems paired hand-crafted colour and motion descriptors chromatic thresholds in the red–yellow band, flicker analysis, optical flow on smoke with Support Vector Machines, but generalized poorly across illumination and camera variation [4]. Shallow CNNs trained on small fire databases then outperformed those baselines despite scarce data [4], and the current wave of ImageNet-pretrained ResNet, DenseNet, EfficientNet, and Vision Transformer backbones reports accuracies above 95% on standard benchmarks [5].

This progress, however, exposed a parallel deficit in trustworthiness. Guo et al. [3] showed that the architectures whose accuracy would justify deployment are also the most poorly calibrated; in safety-critical vision this drove a literature on post-hoc calibration, where Temperature Scaling proved the simplest effective remedy [3]. Bayesian alternatives notably MC Dropout [6] decompose

uncertainty into epistemic and aleatoric components and track empirical error well [6,9]. The explainable-AI toolbox expanded in parallel: Grad-CAM [7] localizes class-discriminative regions without architectural change, while LIME and SHAP add model-agnostic alternatives with different fidelity–interpretability trade-offs [7]. Within wildfire research, explanation has surfaced dataset biases and made model attention legible to non-specialist operators [1]. Even so, explanation, uncertainty, and deployment remain fragmented in the literature usually relegated to ablations rather than woven into the operator-facing path.

3. Materials and Methods

3.1. Dataset and model architectures

The study uses a publicly aggregated wildfire image corpus with binary fire/no-fire labels, spanning varied scenes, backgrounds, and viewpoints to discourage scene-specific memorization. The data are split 70/15/15 (train/validation/test) by stratified sampling, resized to 224×224, normalized with ImageNet statistics, and augmented with random flip, ±15° rotation, brightness/contrast jitter, and random erasing. Three models are trained under one protocol: a Custom CNN of four convolutional blocks (32→64→128→256 channels) with batch normalization, max pooling, dropout (p = 0.5), and a sigmoid head; and ResNet-18 and DenseNet-121, both ImageNet-pretrained with a binary head and fine-tuned at a reduced learning rate. Training uses Adam, binary cross-entropy loss, and early stopping; dropout stays active at inference, so MC Dropout needs no retraining.

3.3. Explainability and uncertainty estimation

Grad-CAM is anchored to the final convolutional block of each network, fusing its feature maps with the back-propagated gradients of the target-class score; the layer is an empirical compromise, since anchoring deeper sharpened flame localization but blurred diffuse smoke. Uncertainty is then estimated in two stages. MC Dropout [6] performs T = 30 stochastic forward passes per input with dropout active; the predictive mean and standard deviation σ give the point estimate and the epistemic-uncertainty proxy:

$$\mu = (1/T)\,\Sigma\, p_t\,, \quad \sigma = std(p_t) \qquad (1)$$

A high σ means the output depends heavily on which weights are silenced a sign that the input lies in an under-represented region of the data manifold. Temperature Scaling [3] handles the complementary problem of systematic overconfidence: the frozen network's pre-sigmoid logits are divided by a single fitted scalar T > 0 that minimizes negative log-likelihood on the validation set. Because the argmax is preserved, accuracy is unchanged while calibration sharpens.

3.4. Deployment and evaluation

The models, the Grad-CAM module, and the uncertainty pipeline are wrapped in a FastAPI service whose /predict endpoint returns the predicted class, the calibrated probability, the MC σ, and a base64-encoded Grad-CAM overlay. A Streamlit dashboard renders each image with its overlay and uncertainty band and colour-codes the response as confirmed fire, confirmed no-fire, or review required against a user-set σ threshold (Figure 1). Evaluation reports accuracy, precision, recall, and F1, plus Expected and Maximum Calibration Error (ECE, MCE) before and after temperature scaling over fifteen equal-width probability bins [9]. Selective Prediction Accuracy is measured at 100/90/80/70% retention, and Grad-CAM quality is judged qualitatively on a stratified sample of correct, false-positive, and false-negative cases, cross-referenced against σ.

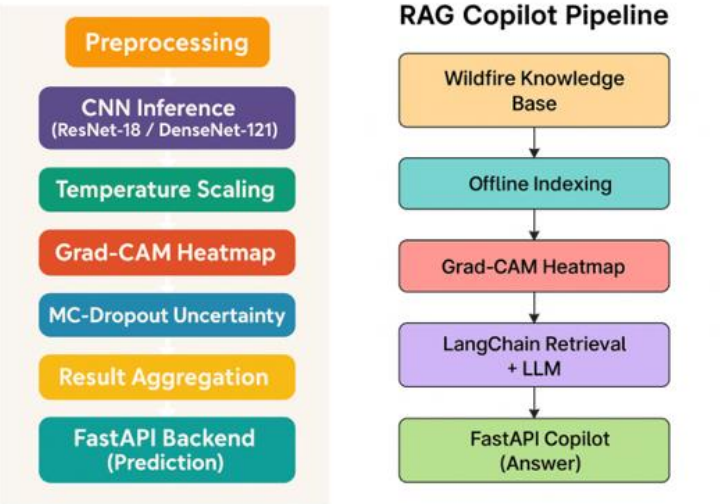

Figure 1. BlazeVeritas AI system architecture and end-to-end workflow.

4. Results and Discussion

4.1. Classification and calibration

Table 1 reports the test-set metrics. ResNet-18 attains the highest accuracy and F1, marginally ahead of DenseNet-121, and both pretrained backbones clearly outperform the Custom CNN confirming the value of transfer learning at moderate label volume. Calibration tells a different story: in raw form all three models are overconfident, the Custom CNN worst (ECE 0.072) and DenseNet-121 best (0.058), with the widest confidence–accuracy gaps in the highest-probability bins. After temperature scaling on the validation set, ECE falls three- to fivefold to 0.018, 0.014, and 0.012 respectively and reliability curves approach the diagonal. The fitted temperatures (≈1.6 for the CNN, 1.4 for ResNet-18, 1.3 for DenseNet-121) indicate that deeper, denser networks start slightly better calibrated, consistent with implicit architectural regularization, yet still gain

from the correction. The predicted class is unchanged for every instance, so the trustworthiness gain costs no accuracy.

Table 1. Test-set classification and calibration metrics for the three architectures.

Model	Accuracy	Precision	Recall	F1	ECE (raw)	ECE (TS)
Custom CNN	0.971	0.989	0.961	0.975	0.072	0.018
ResNet-18	0.999	1.000	1.000	1.000	0.063	0.014
DenseNet-121	0.995	1.000	0.991	0.995	0.058	0.012

4.2. Uncertainty as a deferral signal

MC Dropout σ correlates strongly with classification error: across all three models the median σ on misclassified images is roughly three times that on correctly classified ones. Selective-prediction analysis shows that deferring the 20% most uncertain cases to a human reviewer raises retained-set accuracy by several percentage points, with the largest absolute gain on the Custom CNN the model with the noisiest baseline confidence. Because uncertain predictions are disproportionately wrong, σ becomes an inexpensive, actionable triage signal, and its threshold a tunable knob trading automation throughput against false-alarm rate.

4.3. Explanation quality and decision support

On correctly classified fire images, Grad-CAM reliably settles on the flame core or the dense base of the smoke plume, confirming that the network reads physically meaningful evidence. False positives tell the opposite story: the overlays drift onto sunset clouds, red-roofed buildings, or industrial steam the same spurious cues that defeated handcrafted-feature systems [4] so hidden failure modes become visible at inference time. False negatives cluster on diffuse smoke against bright skies, where the heatmap is flat and σ is elevated; explanation and uncertainty thus reinforce one another (Figure 2). This turns detection into a decision-support task. A bare probability of 0.93 means little, but the same value with a heatmap on a plume and $\sigma = 0.04$ is actionable, whereas 0.93 with $\sigma = 0.18$ and attention on the sky warrants escalation. Even a conservative σ threshold preserves over 80% of throughput while sharpening the precision of auto-confirmed alerts.

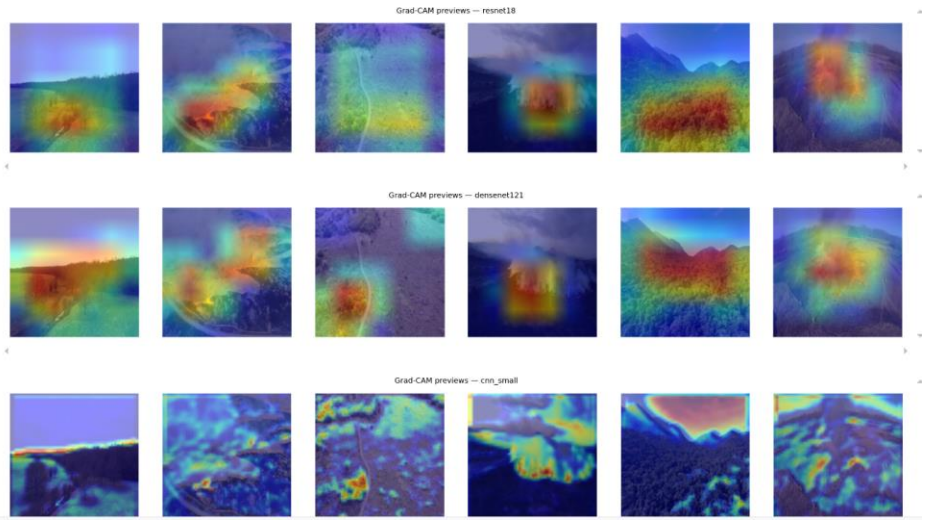

Figure 2. Grad-CAM attention maps across the three models (ResNet-18, DenseNet-121, and the Custom CNN) on representative fire and no-fire images. The pretrained backbones concentrate on flame and smoke regions, whereas the Custom CNN produces diffuse, less focused activations.

5. Conclusion and Future Work

This study has argued that the binding constraint on deploying AI-based wildfire detection is not raw accuracy but trustworthiness, and has presented BlazeVeritas AI as a concrete response: three deep architectures, Grad-CAM explanations, and a calibrated uncertainty pipeline pairing MC Dropout with Temperature Scaling, delivered through a FastAPI/Streamlit stack that treats transparency and calibrated doubt as first-class outputs. Empirically, temperature scaling cuts calibration error three- to fivefold, MC Dropout σ flags misclassifications for review, and Grad-CAM exposes the spurious cues behind residual errors. The novelty lies not in any single technique each is individually established but in their integration into a deployment-ready, decision-support framing. Future work will proceed along three lines: field deployment on operational camera streams to measure domain shift and guide online recalibration; replacing MC Dropout with deep ensembles tighter uncertainty bounds; and extending from binary to multi-class outputs that separate flame, smoke, and false-trigger categories such as steam or sunset glare.

Practical and Theoretical Recommendations

Three recommendations follow from the analysis. (i) Wildfire detectors intended for operational use should be evaluated on calibration metrics Expected and Maximum Calibration Error alongside accuracy and F1, since accuracy alone hides the overconfidence pathology that erodes real-world trust. (ii) Explanation maps and uncertainty estimates should ship as part of the standard inference payload rather than as optional diagnostics, because their

joint availability enables triage rules that no single signal can support. (iii) Procurement and certification frameworks for environmental-monitoring AI should require deployable, audit-ready pipelines in which transparency and calibrated doubt are first-class outputs, aligning practice with emerging regulatory expectations for trustworthy artificial intelligence.

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