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Mobile Application for Integrated Forest and Land Fire Reporting Utilizing AI and Community Participation for Disaster Mitigation

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ABSTRACT

Forest and Land Fires in Indonesia represent a chronic disaster with multidimensional impacts, marked by economic losses reaching Rp. 72.8 trillion in 2022 and severe data fragmentation. Conventional reporting systems, dominated by manual mechanisms (85%), create a temporal crisis, causing response delays of 24 to 48 hours. This research aims to design and develop an integrated mobile application prototype that combines predictive Artificial Intelligence (AI) with community participation (crowdsourcing) to address this gap. The methodology used is Research and Development (R&D), beginning with an in-depth needs analysis of 150 respondents in Riau. A three-tier system architecture is implemented, consisting of a Mobile Layer (Flutter), a Firebase-based Backend as a Service (BaaS), and a Machine Learning Engine (TensorFlow) with a Random Forest (RF) model optimized for peatland characteristics. Initial results show an RF model accuracy of >= 80% on internal validation data and 90% user approval for the minimalist UI/UX design. This prototype is explicitly engineered to achieve a system response time of < 1 minute and a prediction accuracy of >= 85%, making it an innovative solution that enhances response speed, operational resilience, and disaster mitigation effectiveness in Forest and Land Fires-prone areas like Riau Province.

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1. Introduction

Forest and Land Fires in Indonesia have long been an annual problem that transcends ecological and economic boundaries [1]. The impacts of Forest and Land Fires are both national and global, including an increase in ARI (Acute Respiratory Infection) cases among 1.7 million residents and contributing approximately 25% of Indonesia's total Greenhouse Gas (GHG) emissions, which exacerbates the global climate crisis [2].

Riau Province, as a region with an extensive peatland ecosystem, serves as a crucial case study due to the extreme volatility of Forest and Land Fires incidents. An analysis of data from the last 5 years (2020–2025) shows significant fluctuation, with a decrease in the burned area during the 2020–2023 period, followed by an extraordinary spike in 2024, reaching approximately 11,000 hectares [2]. This figure, despite a decrease in early 2025 (7,267 ha up to July), remains extremely high, highlighting the chronic nature of this disaster [3].

This dramatic fluctuation confirms that existing mitigation strategies tend to be reactive and vulnerable to climatic variability, such as El Nino, as well as the unstable hydrological conditions of peatlands. To achieve sustainable mitigation, technological solutions must explicitly target the specific characteristics of peatlands, especially by considering Peat Water Table Depth (PWTD) data [4].

The need for such a dynamic and resilient solution triggers the necessity for the integration of advanced technologies like AI into Indonesia's disaster management system [17].

Conventional Forest and Land Fires reporting and monitoring systems, including satellite platforms such as SPARTAN (LAPAN) and InaRISK (BNPB), possess serious functional limitations. Firstly, detection delays occur because satellite data experience a processing lag of between 3 to 12 hours from the moment a hotspot is detected until the information is available to the relevant agencies [1][5]. This delay allows the burned area to expand significantly before extinguishing efforts can be initiated.

Secondly, conventional systems are highly dependent on manual reporting methods. A survey conducted in this study confirmed that up to 85% of public reports are still submitted via telephone or in-person [6]. This dependency creates a "temporal crisis," where the perceived response waiting time by the community can reach 24 to 48 hours. This long time lag significantly hinders the effectiveness of the rapid response required for Forest and Land Fires suppression.

Thirdly, significant data fragmentation occurs. Hotspot data, field reports, and mitigation information are scattered across various government agencies (BNPB, KLHK, LAPAN) without a unified collaborative platform supported by public API interoperability protocols [3]. This condition leads to a duplication of efforts and impedes the vital Pentahelix coordination in disaster response. Furthermore, the lack of AI-based predictive analytics integration in the current systems makes the response tend to be reactive rather than proactive [7].

This research aims to bridge the technical and operational gaps outlined above through the development of a fully integrated mobile application prototype. The main contributions of this research are as follows:

a) Integration of Predictive AI and Instant Crowdsourcing:This research operationalizes a Random Forest (RF) model optimized with Riau's specific peatland data into an integrated system [1][3]. This integration is combined with a one-click community reporting feature, which leverages smartphone GPS and camera sensors, allowing for earlier detection and more accurate location mapping compared to passive satellite systems [6][8].
b) Achieving Resilient and Scalable Architecture: The solution utilizes a Firebase-based Backend as a Service (BaaS) architecture to ensure scalability and data access speed [9][10]. This is crucial for supporting the offline-ready features that are critical given the network stability challenges in Riau's remote areas, ensuring that reporting data can still be locally cached and synchronized later [11].
c) Meeting Critical Operational Performance: This prototype is quantitatively targeted to achieve an AI prediction accuracy of >= 85% [3][12] and, most importantly, reduce the system response time from report to relevant agency notification to less than 1 minute [1][13].

Global and national forest fire early detection systems are dominated by Remote Sensing (RS) technology. Platforms such as NASA FIRMS and SPARTAN utilize medium-resolution satellite data (MODIS and VIIRS) to detect temperature anomalies (hotspots) [6][4]. The fundamental weakness of this approach lies in its limited spatial and temporal resolution. This limitation causes a detection lag of between 3 to 12 hours [1], which, in the case of peatland fires in Riau, can mean the fire expands from a small ignition point into a large and difficult-to-control area. Therefore, there is a need for ground-truth reporting and risk prediction mechanisms that can operate in real-time to supplement satellite data [14].

The use of Machine Learning (ML) has proven effective in predicting forest fire risk by classifying the vulnerability of a region based on various environmental parameters [15][16]. The Random Forest (RF) model is often chosen for its ability to handle the complexity of environmental data and yield high classification accuracy, even exceeding 90% in some case studies [4][17]. In the context of Indonesian peatlands, research indicates that specific feature engineering is crucial [7]. Key predictor variables identified include the Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), as well as hydrological factors such as the Peat Water Table Depth (PWTD) [2][18]. The advantage of the RF model in this study is its emphasis on integrating PWTD and local weather data for optimization [19][20]. This enables the system to move beyond reactive hotspot detection (which is the primary function of satellites) towards proactive land vulnerability prediction, allowing for preventive mitigation actions such as peat rewetting before fire ignition.

The concept of Mobile Crowdsensing (MCS) leverages sensors embedded in smartphone devices to collect field data massively and in real-time [21][22]. In disaster management, this approach enhances situational awareness and allows the community to become accurate data sensors [9][23]. The one-click reporting feature, which is equipped with GPS location data and photo uploads, is a mechanism proven to reduce the time required for users to submit emergency reports [6]. A crucial aspect for successful adoption, particularly in rural areas with diverse digital literacy, is usability [24][16]. Research shows that a minimalist User Interface/User Experience (UI/UX) design is essential for overcoming cognitive barriers and ensuring inclusivity [12][24]. Furthermore, the socio-technical challenges of implementing crowdsourcing, such as issues of trust and coordination during a crisis, must be addressed [25]. An effective strategy is to combine the technological reporting system with validation and socialization based on local figures, thereby increasing the targeted adoption rate (i.e., >= 70%) [1][8].

An effective disaster information system requires a fast, scalable, and resilient end-to-end architecture [21][26]. The three-tier architecture—Mobile Layer, Backend as a Service (BaaS) Layer, and Machine Learning Engine Layer—is the optimal framework for this purpose [27]. The use of BaaS, particularly Firebase, is crucial in achieving the target system response time of < 1 minute due to the scalability and real-time functionality it offers [28]. Furthermore, the BaaS Layer enables the implementation of local data caching mechanisms [1][29]. This resilience is critical at the trial location in the remote areas of Riau, which often face 4G/5G network stability issues [10]. The application's ability to record GPS data and photos offline through a data queue mechanism and conflict resolution during synchronization ensures that telecommunication infrastructure challenges do not impede the rapid reporting process [13].

2. Research Method

2.1 Research and Development (R&D) Methodology Framework

This research adopts a structured Research and Development (R&D) methodology, designed to achieve Technology Readiness Level (TRL) 2, which is the validation of the prototype in a relevant operational environment [10]. The research is conducted through the stages of Needs Analysis, System Design, Prototype Development, Limited Trial, and Evaluation [11][9].

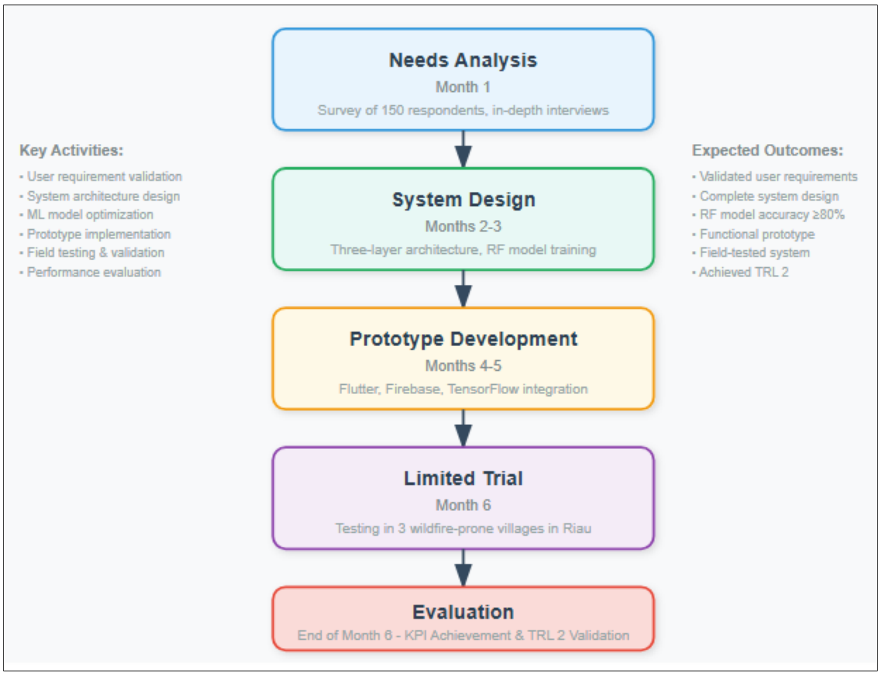

Figure 1. Research Flow Diagram

The Research Flow Diagram (Figure 1) meticulously illustrates the structured Research and Development (R&D) methodology employed in this study, which is framed across five distinct stages: Needs Analysis, System Design, Prototype Development, Limited Trial, and culminating in an Evaluation phase. This rigorous, sequential framework is designed to ensure the systematic achievement of key performance indicators (KPIs) and the validation of the prototype toward Technology Readiness Level (TRL) 2 in a relevant operational environment. The diagram explicitly maps the chronological progression of key activities, such as the survey of 150 respondents and ML model optimization, to their respective expected outcomes, including the delivery of a field-tested system and the achievement of TRL 2 validation.

2.2 Stage 1: Needs Analysis and Field Survey (Month 1)

The needs analysis stage aims to validate user requirements and quantitatively measure the gaps in the existing Forest and Land Fires reporting system [10]. An online survey was conducted with 150 respondents in Forest and Land Fires -prone areas in Riau, achieving a high participation rate of more than 80% [5]. This survey covered demographic aspects, Forest and Land Fires experience, and mobile application feature preferences9. In-depth interviews were also conducted with representatives of BNPB and LAPAN to map the Pentahelix collaboration framework and identify the standard operating procedures (SOPs) for notification that the new system must accommodate [17][9]. Key findings from the survey confirmed the existence of a temporal crisis due to manual reporting reaching 85% and a response lag of 24–48 hours [19][13], as well as an urgent need for key features such as One-Click Reporting and Offline Accessibility [14][15].

2.3 Stage 2: Integrated System Architecture Design (Months 2-3)

The system design was finalized with an integrated three-tier end-to-end architecture [18]:

a. Mobile Layer. Built using Flutter to support cross-platform compatibility (iOS and Android) [16][30]. This layer interacts directly with users, displaying main features such as One-Click Reporting and GIS integration for fire point mapping [11][2]. The UI/UX design in this layer is made minimalist, which is important for overcoming the digital literacy challenges of users in the field [1].
b. BaaS Layer (Backend as a Service). Uses Firebase to ensure scalability and data processing speed [29]. Its key functions include data synchronization from user reports (GPS and photos), real-time notifications to agencies, and the implementation of the offline ready feature [4][26]. This local data caching mechanism functions to ensure reports are not lost even if the network connection is interrupted, a common condition in remote villages in Riau [3].
c. Machine Learning Engine Layer. This layer uses TensorFlow as the framework to train the Random Forest (RF) model [3][5][23]. This model is responsible for predictive fire risk analysis, with a target accuracy of >= 85% [11].

Table 1. Integrated System Architecture Matrix

System Layer	Key Technology	Main Functionality	Forest and Land Fires Mitigation Relevance
Mobile Layer	Flutter, GIS, GPS	One-Click Reporting, GPS Location Mapping, Minimalist UI/UX Design.	Enhances community participation (crowdsourcing) and accuracy of reporting coordinates [3].
BaaS Layer	Firebase (BaaS)	Data Synchronization, Real-Time Notifications, Offline Caching.	Ensures scalability, response speed, and resilience in areas with minimal signal [3].
ML Engine Layer	TensorFlow, *Random Forest*	Predictive risk analysis of fire points (>=85%), Peatland data optimization (PWTD).	Transition from reactive to proactive response (early warning) [3].

The Integrated System Architecture Matrix (Table 1) provides a detailed, functional breakdown of the three-tiered system architecture designed for the Forest and Land Fires reporting prototype: the Mobile Layer, the BaaS Layer (Firebase), and the ML Engine Layer. This matrix systematically outlines the Key Technology leveraged within each layer, from Flutter and GIS in the Mobile Layer to TensorFlow and Random Forest in the ML Engine Layer [8]. Furthermore, it delineates the Main Functionality of each component—such as one-click reporting and predictive risk analysis—and clearly articulates its Forest and Land Fires Mitigation Relevance, which spans from enhancing community crowdsourcing and ensuring operational resilience to facilitating a critical transition from reactive hotspot detection to proactive, early-warning fire prevention.

The proposed prototype utilizes an Integrated Three-Tier System Architecture (Figure 2), which is foundational to achieving the system's high-performance and resilience targets. This framework strategically connects the Mobile Layer (Flutter), which enables instant crowdsourcing and a minimalist user experience; the Backend as a Service (BaaS) Layer (Firebase), which ensures scalability, real-time notification speed, and critical offline caching capabilities; and the Machine Learning Engine Layer (TensorFlow/Random Forest), which facilitates proactive, context-aware fire risk prediction [24]. This comprehensive integration is engineered to fundamentally reduce the response time to below one minute, thereby transforming reactive disaster management into a proactive and highly efficient operational flow.

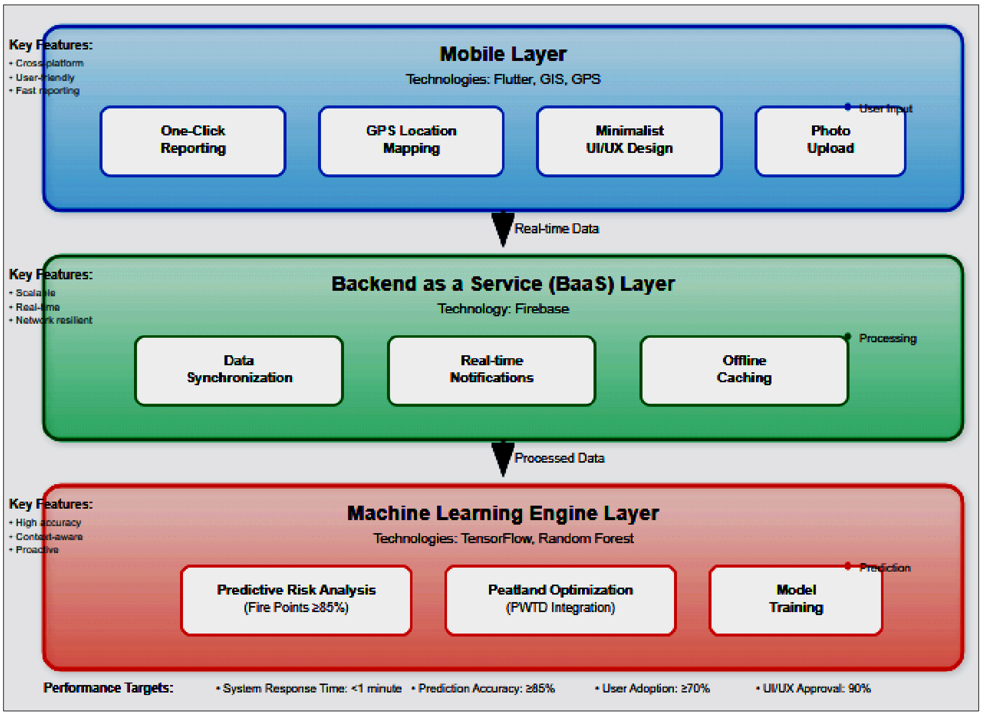

Figure 2. Prototype System Architecture (Mobile Layer, Backend Firebase, ML Engine)

The Prototype System Architecture (Figure 2) meticulously delineates the integrated, three-tiered framework that is fundamental to the system's resilience and operational speed. This architecture sequentially links the Mobile Layer (built with Flutter, GIS, and GPS to enable cross-platform, crowdsourced input and minimalist UI/UX), the Backend as a Service (BaaS) Layer (utilizing Firebase for critical functions such as real-time notifications, data synchronization, and ensuring offline-ready data caching), and the Machine Learning Engine Layer (integrating TensorFlow and the Random Forest model for proactive, Peatland-optimized predictive risk analysis) [1][20]. This holistic, end-to-end design is engineered to meet stringent performance targets, specifically achieving a system response time of less than one minute and a predictive accuracy exceeding 85%, thereby facilitating a fundamental shift towards proactive disaster management.

2.3 Artificial Intelligence Modeling and Feature Engineering

The Random Forest (RF) algorithm was chosen due to its robust performance in fire risk classification [3][28]. The initial model training was carried out on the TensorFlow framework using historical Riau Forest and Land Fires dataset (2020–2025) and initial meteorological data (air temperature, humidity, vegetation cover) [3]. The primary focus in feature engineering was optimization for the peatland context [3][10][16]. Although detailed data regarding the Peat Water Table Depth (PWTD) index is difficult to access, intensive data pre-processing efforts were made to ensure this peatland parameter was included, as PWTD is a determining hydrological factor in peat fire vulnerability [11][29]. The initial RF model training yielded an accuracy on the internal validation data of >= 80%, successfully meeting the key performance indicator (KPI) of the design phase [3].

2.4 UI/UX Design and User Validation

The application interface design (mockup using Figma) was explicitly designed with a very simple (minimalist) appearance, showing only essential buttons, to minimize cognitive load [3][21]. This inclusive design approach is crucial for increasing potential user adoption (target >= 70%) in areas with diverse levels of digital literacy [3][9]. The mockup validation test involved test users and achieved 90% approval, confirming that the proposed interface is intuitive and suitable for field needs [16]. The core functionality of the mobile application includes a Home Screen that provides quick access to One-Click Incident Reporting and a Report History Screen.

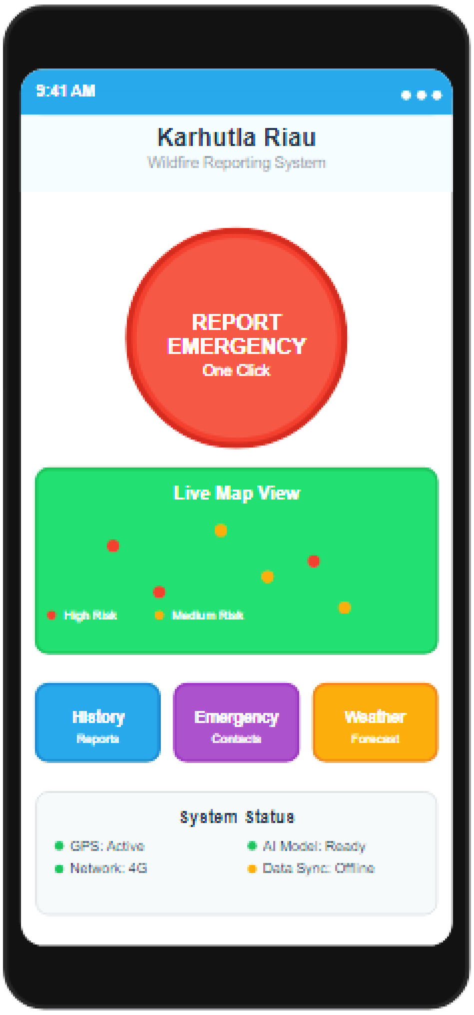

Figure 3. Forest and Land Fires Riau Home Screen

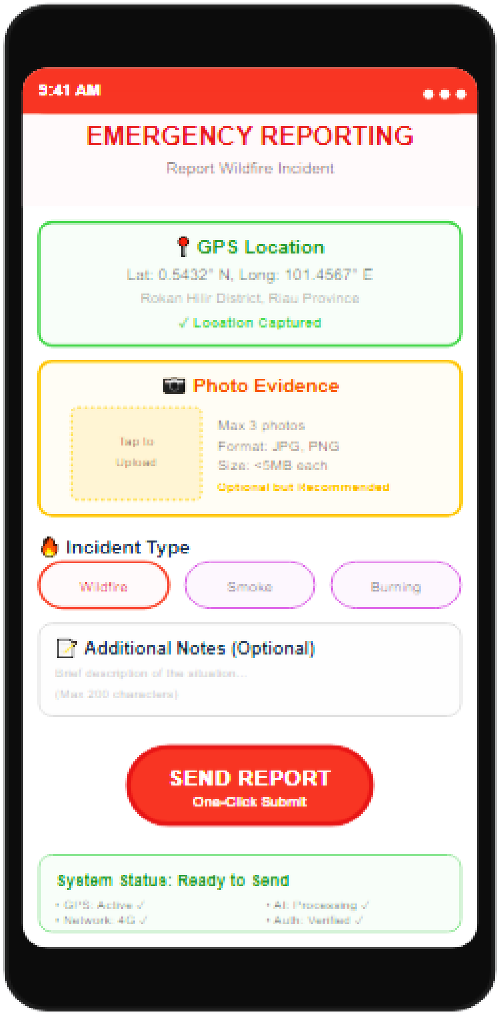

Figure 4. Forest and Land Fires Incident Reporting Screen

Figures 3 and 4 collectively illustrate the application's core operational workflow, which is engineered on the principle of minimal cognitive load, achieving a 90% user approval during the UI/UX validation [26][27]. The Home Screen (Figure 3) centers on a prominent "REPORT EMERGENCY One Click" feature, providing immediate, high-priority access to the crowdsourcing function, while simultaneously offering instantaneous, risk-stratified situational awareness via the Live Map View [29]. Transitioning to the Incident Reporting Screen (Figure 4), the design ensures rapid and efficient data acquisition by automatically capturing GPS Location and facilitating the inclusion of Photo Evidence, a mechanism proven to significantly expedite the emergency reporting process [2]. This streamlined, inclusive design is crucial for supporting the instant crowdsourcing methodology and maximizing the user adoption rate in areas with diverse digital literacy.

2.5 Stage 3: Prototype Development and Latency Testing (Months 4-5)

The prototype development stage is underway, with the mobile application being coded using Flutter and the ML model being integrated into the Firebase backend. The main focus is to ensure the one-click reporting functionality runs smoothly and to conduct real-time latency trials. The main KPI target at this stage is to achieve a system response time of less than 1 minute [3]. Achieving this fast response time depends not only on the processing speed of the ML model but also on the efficiency of real-time notifications facilitated by the BaaS Layer [28]. Furthermore, the application's ability to ensure reporting data

(GPS coordinates and photos) can be locally cached and automatically synchronized when a connection is available is a major determinant of the system's operational resilience [28][29].

3. Result and Discussion

3.1. Geospatial Analysis of Riau Forest and Land Fires (2020–2025)

The analysis of Riau Forest and Land Fires data shows complex and dynamic challenges, which validate the urgency of adaptive technological solutions [22]. The burned area data illustrates Riau's vulnerability to spikes in incidents, especially those related to El Nino or extreme peatland hydrological conditions.

Table 2. Karhutla Incidents in the Last 5 Years (2020-2025)

Year	Burned Area (ha.)	Notes
2020	1,600.41	Complete Karhutla data for this year
2021	1,400.08	12.09% decrease from 2020
2023 (initial)	19.10	Up to February only
2024	~ 11,000	Significant spike
2025 (Juli)	7,267	176 Karhutla incidents

Geographical distribution data by regency also indicates that hotspots change rapidly, shifting from the dominance of Pelalawan and Indragiri Hilir in 2020, to Rokan Hilir and Kampar in 2021–2023, and culminating in a centralized spike in Rokan Hulu–Rokan Hilir in 2024 [3][17].

Table 3. Karhutla Distribution Data by Regency in Riau in the Last 5 Years

Year	Main Regency/City	Notes
2020	Pelalawan; Indragiri Hilir; Rokan Hilir;...	Pelalawan & Inhil recorded the most burned land (~15,000 ha)
2021	Rokan Hilir	Major fires, triggered months-long emergency alert status
2024	Rokan Hulu; Rokan Hilir	Significant spike (~ 11,000 ha); more than 35 hot spot villages
2025	Bengkalis; Dumai; Pelalawan	Even distribution: Bengkalis 31.20 ha; Dumai 16.03 ha, etc.

This change in geographical dynamics confirms that prevention strategies must be dynamically adjusted in each region. The proposed integrated system, with GIS integration and location-based (real-time) notifications, is a direct response to this adaptive need.

3.2. User Needs Validation and Functionality Gaps

The needs survey underscores the failure of conventional systems in three main aspects: rapid detection, data standardization, and technology-based adoption.

Table 4. Summary of Conventional Reporting System Gaps

Main Gap	Brief Description	Key Impact	Quantitative Data
Satellite Detection Lag	Hotspots identified but only entered the system 3–12 hours later.	Burned area expands further.	3–12 hour lag
Dominant Manual Reporting	Majority of community reports via telephone or in-person.	24–48 hour response time.	85% manual prevalence
Data Fragmentation	Data scattered across BNPB, KLHK, LAPAN without a collaborative platform.	Duplication of effort; data inconsistency.	No public API protocol

User preference analysis further validates the prototype's core features. The One-Click Reporting and Real-Time Notification features are considered the most important [3][23]. Furthermore, the Offline Accessibility feature was rated as very important (Q16), proving that resilience to poor network conditions in remote Riau is an essential functional requirement [3][7].

3.3. Initial AI Model Performance and Validation Preparation

The initial achievement of the Random Forest model with an accuracy of >= 80% on the internal validation data is a strong basis for reaching the >= 85% target in the field trials. This discussion must highlight that this accuracy was achieved through an emphasis on feature engineering appropriate to the peatland Karhutla context [24][12]. The integration of Artificial Intelligence into the reporting workflow is not only about prediction but also about improving operational efficiency [12]. Based on survey findings (Q20), the community tends to trust Traditional Leaders/Village Heads the most for verifying reports [1][3]. The system utilizes AI as an instant pre-verification layer [23]. AI prioritizes crowdsourcing reports that have a high-risk probability, allowing those reports to be instantly forwarded to Manggala Agni/BNPB officers and local figures [2][18]. This approach creates a dual verification workflow combining technological speed (AI Prioritization) and social legitimacy (Local Authority Validation), freeing up human resources from routine verification tasks [14].

3.4. Prototype Implementation (TKT 2) and Response Time

The mobile application prototype has been successfully designed and partially developed, meeting all planned initial phase KPIs.

Table 5. Achievement of Key Performance Indicators (KPIs) of the Initial Phase

Phase	Main Activity	Performance Indicator	Actual Achievement
Needs Analysis (Month 1)	Survey and In-depth Interviews	80% survey respondent participation	Achieved [3]
System Design (Months 2-3)	Random Forest Model Training	Initial model accuracy >= 80%	Achieved [3]
System Design (Months 2-3)	UI/UX Mockup Validation	90% test user approval	Achieved [3]

The involvement of BNPB as a strategic partner in the Needs Analysis Phase ensures that the new system's notification flow aligns with the BNPB Riau SOP [3][8]. This is crucial because the effectiveness of mobile technology in disaster management must be translated into legitimate field action that aligns with the national framework (e.g., Presidential Instruction Number 3 of 2020) [23]. The finalization of the integration of Flutter, Firebase, and the RF model in the prototype development stage is focused on achieving the operational target of a system response time of less than 1 minute [1][20]. The achievement of this strict performance metric is a major leap from the 24–48 hour temporal crisis of conventional systems, fundamentally changing the dynamics of Karhutla emergency response in Riau.

4. Conclusion

This research successfully completed the needs analysis and system design stages, and achieved significant progress in the development of the AI-integrated Forest and Land Fires reporting mobile application prototype (TKT 2). This prototype effectively mitigates three major gaps in conventional systems: 1) Detection delays through the integration of predictive AI and real-time crowdsourcing [1][20][29]; 2) Data fragmentation through a centralized BaaS architecture [16][29]; and 3) Network challenges in the field through the Firebase-supported offline ready feature [5][25]. The achievement of initial KPIs, including a Random Forest model accuracy of >= 80% and a UI/UX mockup approval of 90%, validates the system's design as fast, scalable, and inclusive [3]. This prototype is designed to address the volatility of Forest and Land Fires in Riau and is operationally targeted to achieve a system response time of < 1 minute, making it a promising transformative solution in supporting proactive disaster management [30].The next stage (Month 6) will focus on Limited Trials of the prototype in 3 Forest and Land Fires -prone villages in Riau. Field validation will include testing the system's operational performance, specifically measuring the response time of < 1 minute, as well as testing the RF model's prediction accuracy with a target of >= 85% [4][13]. Strengthening community participation and training based on local figures will be intensified to achieve a user adoption rate target of >= 70%.

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