



Development of Post Fire Severity Assessment Module in Indonesian Forest and Land Fire Prevention Patrol System

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Abstract

The severity of forest and land fires is a crucial indicator for assessing their impact on ecosystems, particularly vegetation and soil. The assessment results serve as a foundation for forest and land restoration, rehabilitation, and conservation efforts. This study employs a deep learning algorithm to develop a forest and land fire severity assessment module. The CNN model used is MobileNetV2 that has an accuracy of 88.8%. The smart module is integrated into the Indonesian Forest and Land Fire Prevention Patrol Mobile Application and follows the Software Development Life Cycle approach in its development. Field observation images are input to the CNN module in the mobile application. The module then analyzes the fire severity and classifies it into very light, light, moderate, severe, and very severe categories. Testing results indicate that the module accurately predicts fire severity based on established assessment standards. The optimal time for capturing images is a few days after the fire, during daylight hours, to ensure the majority of images depict burned areas. Additionally, the findings highlight that lighting conditions and image quality significantly influence the accuracy of severity predictions. Further development is required to enhance the module's compatibility and flexibility, enabling its use across various devices.

Keywords: deep learning, fire severity, mobile application, SIPP karhutla

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Introduction

Forests are complex ecosystems comprising various natural resources and environmental components, including plants, animals, and microorganisms, which interact in an inseparable manner (Oswalt et al., 2019). Depending on its nature and intensity, an ecosystem can be degraded or entirely lost when subjected to one or more destructive factors (Kumar et al., 2022). Among the primary drivers of forest and land degradation, fire is a significant factor contributing to forest destruction (Heidari & Arfania, 2022). Forest and land fires (*karhutla*) result from human activities or natural phenomena, characterized by the rapid spread of fire and the burning of forests and land along its path. Over the past decade, there has been a notable increase in both the frequency and intensity of forest fires worldwide, raising serious concerns about their long-term environmental and socio-economic impacts (Tariq et al., 2021). The effects of global warming—particularly rising temperatures, changes in rainfall patterns, and declining soil moisture levels—suggest that the frequency and extent of forest fires are expected to continue increasing globally (Westerling, 2016). Indonesia, home to vast forested areas, has also been significantly impacted by forest and land fires. The country's forest cover has been shrinking annually, with the Ministry of Environment and Forestry reporting that in 2023 alone, forest fires

affected approximately 1,161,192.90 ha of land (Sipongi, 2023). Several provinces in Indonesia are particularly prone to forest and land fires, including South Sumatra, Riau, Jambi, Central Kalimantan, and South Kalimantan. These regions have been implementing fire prevention and control measures since the beginning of the year to mitigate the risks associated with recurring wildfires (Budiningasih et al., 2022).

Forest and land fire control has become a key priority for the Indonesian government, leading to the issuance of Regulation of the Minister of Environment Number 32/2016 on Forest and Land Fire Control. In response, the Ministry of Environment and Forestry (KLHK) established Manggala Agni, a specialized national organization responsible for forest and land fire management (Rauf et al., 2020). Manggala Agni consists of trained firefighters and operational personnel dedicated to fire prevention, suppression, and mitigation efforts (Sitanggang et al., 2022). To enhance operational efficiency and data management, KLHK developed the Forest and Land Fire Prevention Patrol Information System (SIPP *karhutla*), a mobile-based application designed to document all fire control activities conducted by Manggala Agni (Sitanggang et al., 2022). One of the key functionalities of this system is post-fire field observation, which provides crucial data for assessing fire

severity. These observations serve as essential inputs for measuring the extent and impact of forest and land fires (Syaufina et al., 2021).

The severity of forest and land fires is a critical indicator for evaluating their environmental impact, as fires can cause both direct and indirect damage to vegetation and soil, depending on their intensity and frequency (Jhariya & Singh, 2021). Assessing fire severity is essential for fire recovery planning, forest conservation efforts, and law enforcement related to land use and fire prevention (Syaufina et al., 2021). Previous studies have developed methods for fire severity assessment, such as the approach by Syaufina and Hamzah (2021), which utilized an aggregate scoring system based on vegetation and soil conditions as key criteria. However, conducting direct field measurements is often time-consuming and costly, particularly in remote fire-affected areas. A more efficient alternative is the use of image-based technology for severity assessment (Arrafi et al., 2022). Advancements in deep learning and computer vision have enabled automated fire severity analysis using image data. One of the most effective approaches involves the use of Convolutional Neural Networks (CNNs), which are widely applied for object detection and image classification in various domains (Ghali & Akhloufi, 2023). CNNs can process post-fire images to assess fire severity with high accuracy, reducing reliance on manual field inspections (Taye, 2023). Among CNN architectures, MobileNetV2 has emerged as a leading technology for fire severity classification due to its computational efficiency and lightweight design (Dong et al., 2020). MobileNetV2 utilizes Depthwise Separable Convolutions (DSC) to optimize performance while maintaining high accuracy. This model is particularly well-suited for real-time applications on mobile devices, enabling rapid analysis in field conditions (Intaraprasit et al., 2023). Moreover, MobileNetV2 offers a balance between performance and resource efficiency, requiring minimal storage and computational power compared to more complex deep-learning models (Roh et al., 2022).

This CNN-based model can be integrated into the SIPP *karhutla* mobile application to analyze the severity of forest and land fires. The model is implemented as a module through a structured system development process. The software development life cycle (SDLC) methodology is employed in this study, encompassing key phases such as planning, analysis, design, development, and testing. The SDLC approach ensures a systematic, measurable, and efficient software development process (Yaz et al., 2023). A well-executed SDLC reduces the risk of errors, enhances quality control, and delivers a reliable and user-centered solution that meets the needs of both users and stakeholders (Maryani et al., 2022). In this study, the SDLC framework facilitates the seamless development of the forest and land fire severity assessment module, which is fully integrated into the SIPP *karhutla* mobile application. This study aims to develop and implement a forest and land fire severity assessment module within the SIPP *karhutla* mobile application, utilizing a pre-trained MobileNetV2 model for fire severity prediction. The module has undergone testing and is expected to provide accurate and reliable predictions regarding fire severity levels. Beyond its technical contri-

butions, this study seeks to generate valuable data and recommendations for the Ministry of Environment and Forestry (KLHK). The insights derived from this system can assist policymakers in formulating effective post-fire rehabilitation and land restoration programs, ultimately enhancing Indonesia's forest and land fire management strategies.

Methods

This study employs a methodological approach that involves the development of intelligent modules and the application of the MobileNetV2 model. The research follows a structured process to build a forest and land fire severity analysis module using field observation images. To ensure an efficient, systematic, and controlled development process, the SDLC approach is applied in developing this CNN-based module. The research methodology focuses on identifying developer requirements and structuring the module development into the following key stages: planning, analysis, design, development, and testing. The detailed implementation of these stages is illustrated in Figure 1.

Identification of module development requirements The identification phase aims to determine the requirements needed to develop the module for assessing fire severity in forests and land. This includes selecting the appropriate deep learning model to be integrated into the existing system and defining both functional and non-functional requirements. Functional requirements define the essential system features that fulfill user needs. These include processing field observation images, analyzing fire severity levels, and classifying fires into very light, light, moderate, severe, and very severe categories (Saroja & Haseena, 2023). Non-functional requirements relate to system quality attributes such as performance, security, reliability, and scalability, ensuring that the module operates efficiently under various conditions (Sherif et al., 2023).

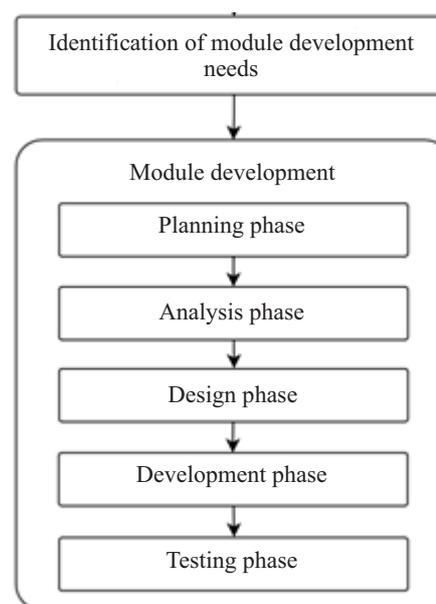


Figure 1 The research framework and methodology.

Planning phase The planning phase serves as the foundation for module development, outlining the objectives, scope, and system requirements. This stage involves defining the development goals and identifying the necessary resources to ensure a structured and goal-oriented module development process.

Analysis phase During the analysis phase, user needs are systematically identified and examined. This involves gathering information to understand the context and purpose of the module (Pinciroli et al., 2022). Functional aspects: Users must be able to capture post-fire images, submit them through the application, and receive automated severity classification results. Non-functional aspects: The classification process must be fast and accurate, ensuring real-time usability for field operations.

Design phase The design phase focuses on developing the system architecture and user interface based on the analysis results (Olorunshola & Ogwueleka, 2022). Key aspects include: Integration into the existing application: The classification module is embedded within the SIPP *karhutla* mobile application. Image processing workflow: Users take photos using their smartphone camera, which are then uploaded to a server and processed by the classification model. User experience (UX) considerations: The interface is designed for ease of use, allowing quick and intuitive interaction with classification results.

Development phase The development phase involves the implementation of the module, including: Application programming interface (API) development: An API is created to handle image uploads, send images to the classification model, and return results to the user. User interface (UI) integration: The UI is developed to seamlessly fit within the existing SIPP *karhutla* application, ensuring a smooth transition from image capture to severity classification.

Dataset description The data collected in this study consisted of an image dataset of areas after forest and land fire management. The data were obtained from the Forest and Land Fire Prevention Patrol System (<https://sipongi.menlhk.go.id/sipp-karhutla/>) and shutterstock.com. The dataset covers a variety of post-forest and land fire conditions, comprising 560 images from various forest fire incidents in Indonesia.

Model development and fine-tuning This study uses the MobileNetV2 architecture to create a classification model. During the training process, the final layer of MobileNetV2 was frozen to allow for the addition of new layers appropriate for forest and land fire image classification. The hyperparameters in this model are tuned using the grid search technique, where several hyperparameter combinations are tested to find the most optimal combination, the combinations are Batch Size [8, 16, 32], Learning Rate [0.0001, 0.00001], and Dropout [0.3, 0.4, 0.5]. Model training using 50 epochs and a dense layer of 512. Based on the results of model training using grid search, the most optimal parameters in this study were as follows: `batch_size`

= 16, `learning_rate` = 0.0001, and `dropout` = 0.3. This parameter combination resulted in an accuracy of 88.8%, with a precision of 90.6% and a recall of 85.3%. The optimal model training process was evaluated using a confusion matrix to analyze its performance in classifying five categories of forest and land fire severity. The visualization of the confusion matrix resulting from the model evaluation can be seen in Figure 2.

Quantitative validation and error analysis The confusion matrix analysis (Figure 2) provides a detailed breakdown of the model's classification performance for each severity class. For the very light category, the model correctly classified 33 out of 36 images (91.7%), with 3 images misclassified as light. In the light category, 36 out of 41 images (87.8%) were correctly identified, while 5 images were misclassified as very light. For the moderate class, the model achieved 92.3% accuracy (24/26 images), with one misclassification to severe and one to light. In the severe category, only 23 out of 31 images (74.2%) were correctly identified, with most misclassifications being confused with moderate severity (6 images) and a smaller portion with very severe (2 images). The very severe category demonstrated perfect classification accuracy, with all 36 images correctly identified (100%). This misclassification pattern reveals that the most challenging cases occur between adjacent severity levels, such as moderate vs. severe and very light vs. light. These errors are often due to overlapping visual features, e.g., partial burn marks obscured by vegetation or lighting conditions that alter the apparent darkness of the soil.

Comparison with basic methods for model reliability To quantitatively verify model performance, we conducted benchmark tests against two simple baselines: a random guess (expected accuracy of 20%) and a majority class baseline (expected accuracy of 24.1%). With an average validation rate of 88.8% across 170 images, a one-sample binomial test against the baselines mostly showed highly significant differences ($p \approx 1.85 \times 10^{-71}$). The 95% Wilson confidence interval for model accuracy ranged from 83.2 to 92.7%, confirming the statistical superiority of the model. Prediction reliability was evaluated using Cohen's κ between

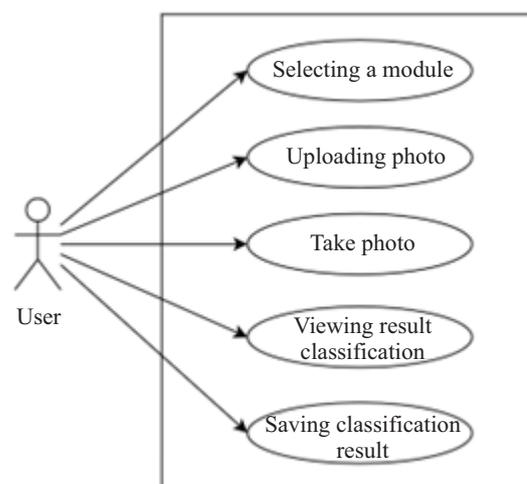


Figure 2 Use case diagram.

the model results and the expert reference labels on the validation data, yielding a value of 0.867, which is considered nearly perfect. This figure demonstrates excellent agreement between the model and the manual assessment.

Testing phase The testing phase ensures that the module meets functional and non-functional specifications (Taley, 2020). The testing process is carried out on the backend service to ensure that the system can receive photos, send them to the model, and manage the results correctly. It also tests the functionality and performance of the feature that classifies fire severity based on photos and ensures that the user interface functions appropriately.

By following this structured development approach, the forest and land fire severity module can be effectively integrated into the SIPP *karhutla* mobile application, enhancing real-time fire monitoring and post-fire assessment capabilities.

Results

The findings of this study begin with the identification of functional and non-functional requirements for developing the forest and land fire severity analysis module within the SIPP *karhutla* application. The functional requirements for this classification module encompass several key aspects, which are detailed in Table 1. These requirements define the essential system capabilities, ensuring that the module

effectively supports fire severity assessment based on field observation images.

Non-functional requirements are criteria or constraints that define how the system works. Table 2 indicates that these requirements are focused on the quality and performance of the module.

The planning begins with a discussion with the SIPP *karhutla* development team regarding the needs and objectives of adding new features to the application. This discussion aims to ensure that the innovations implemented can support Manggal Agni's operational activities and meet the needs of effective forest and land fire control. Based on the discussion results, planning features were integrated into the application, namely the module for analyzing forest and land fire severity, integration of photo taking and image uploading, interaction with the backend system, and data storage in the database.

The analysis stage in the module development process was carried out by considering user needs and the data characteristics used. Currently, the SIPP *karhutla* application is operational and used by patrol teams in the field. Several modules, such as Patrol Activities and Reporting, are running well. One of the modules in this application is Observation, which is used to record field observation results. In this study, the feature for adding fire suppression data, in documenting photos of the area after suppression, a new module was added, namely the forest and land fire severity module using

Table 1 Functional requirements of the module

Functional requirements	Analysis results
Identify five image classes	The classification module must be capable of categorizing post-forest fire area images into five severity levels: very light, light, moderate, severe, and very severe. This functionality is crucial, as each category reflects a distinct level of fire impact, which informs appropriate response and recovery measures.
Photo taking capabilities	To achieve this, the module must:
Fast and accurate classification	Support multiple image input sources, allowing users to either upload images from their device or capture photos directly using the in-app camera feature.
Integration	Process and analyze images efficiently to classify fire severity levels with high accuracy.

Table 2 Non-functional requirements of the module

Non-functional requirements	Analysis results
Processing speed	The module must be able to process images quickly, ideally within seconds, to meet operational needs in the field. This processing speed is important to support rapid response in forest and land fires.
Scalability	The module must be able to handle large data volumes, considering the number of images that may be received and processed can be very large, especially during the dry season. The module must be able to function properly even if the amount of data significantly increases.
Reliability and availability	The module must be reliable and always available to support all ongoing operations.
User experience	The user interface must be easy to understand and use so that patrol teams in the field can efficiently use this module.
Data handling capacity	The module must handle various sizes and resolutions of images from multiple sources.

the MobileNetV2 model. The process begins when the user opens the SIPP *karhutla* mobile application and selects the option to make an Observation, then selects the Add Fire Suppression Data feature and does the documentation.

Furthermore, the user can select a photo from the gallery or use a smartphone camera to take a new photo. This photo is uploaded to the system as input to be processed further. After the photo is input, the classification module based on the MobileNetV2 model begins processing the image. This classification process involves several stages of image processing to extract features and identify the appropriate forest and land fire severity class. After completing the classification process, the results are displayed on the user's smartphone screen. These results include prediction classes that indicate the severity of forest and land fires, for example, Low, Moderate low, Moderate, Moderate high, or High, along with probabilities that indicate the model confidence level in the prediction. After the classification results are displayed, the process is complete.

Further analysis uses the unified modeling language (UML) diagram to model the workflow from image input to classification result output. This process aims to ensure that the classification module can be integrated well into the SIPP *karhutla* application by clarifying the data flow and processes that occur in the system. The use case diagram is presented in Figure 2.

Based on the use case diagram in Figure 3, actors consisting of Mangala agni or the patrol team and operational personnel in the field can perform several tasks, such as selecting a classification module and then uploading photos from the gallery or taking photos directly using the camera, after that, users can view the classification results and save them in the database.

The application architecture and user interface have been designed to ensure ease of use. This design includes integrating the classification module with existing applications and the process of taking photos, uploading, and receiving classification results. The application architecture design for the classification module can be seen in Figure 3.

The new architectural design for this module ensures that each component works synergistically, allowing users to interact through the application on their smartphone. SIPP

karhutla functions to observe and document forest and land fires, connecting to the backend system via Rest API. The internet is the connecting medium for uploading images and retrieving classification results. Rest API acts as a bridge between the application and the server, allowing data to be sent and received. The Web Server handles requests from the Rest API and interacts with the database for data storage and retrieval. The database stores the required data, sends data when the Web Server requests, and stores new data generated. The next stage is designing a user interface that focuses on ease of use. The interface is simple, with clear and responsive navigation to ensure a positive user experience. The module interface design can be seen in Figure 4.

Based on the application interface design in Figure 4, the feature to photograph or select an image from the gallery has a simple and functional layout. Users can access the smartphone camera to take a new photo or choose a picture from an existing gallery. The classification results are displayed with a severity category label and equipped with a probability indicating the model confidence level in the prediction.

The development stage in this study is to implement the results of the analysis and design done in the previous stage. The discussion results with the backend infrastructure development team are in the observation table in the section adding fire suppression data; two data attributes are added, namely prediction_results and probability. These two attributes are used to store the image classification results taken by the patrol team in the field, and the data will be stored in the database through the Rest API process. The next stage is the implementation of the MobileNetV2 model on mobile devices. This process involves pre-processing images taken by the user, feature extraction using the MobileNetV2 model, and predicting the severity class of forest and land fires. The model is stored on the device, so the classification process can be done faster without sending images to the server, increasing the application's responsiveness, especially in locations with limited internet connectivity. After the classification, the results are sent to the backend server via the real-time API. This allows the classification results to be stored for future analysis or reporting needs.

The testing phase in this study involves various aspects

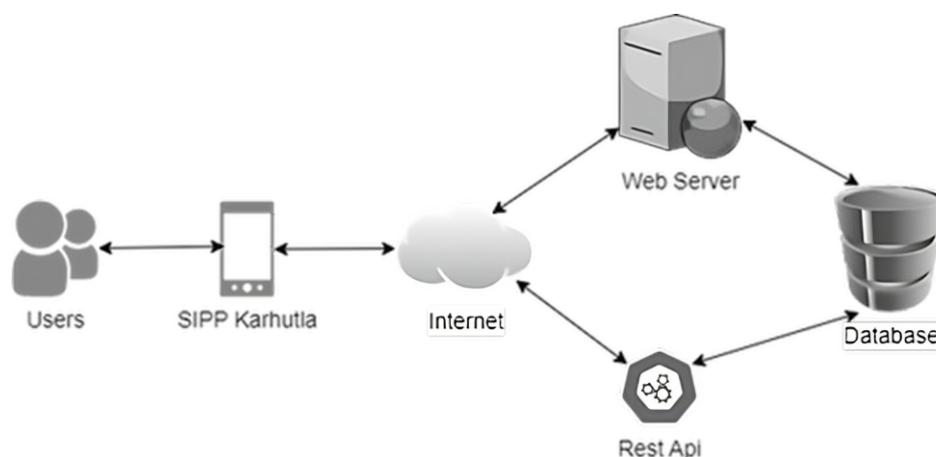


Figure 3 Architectural design for modules.

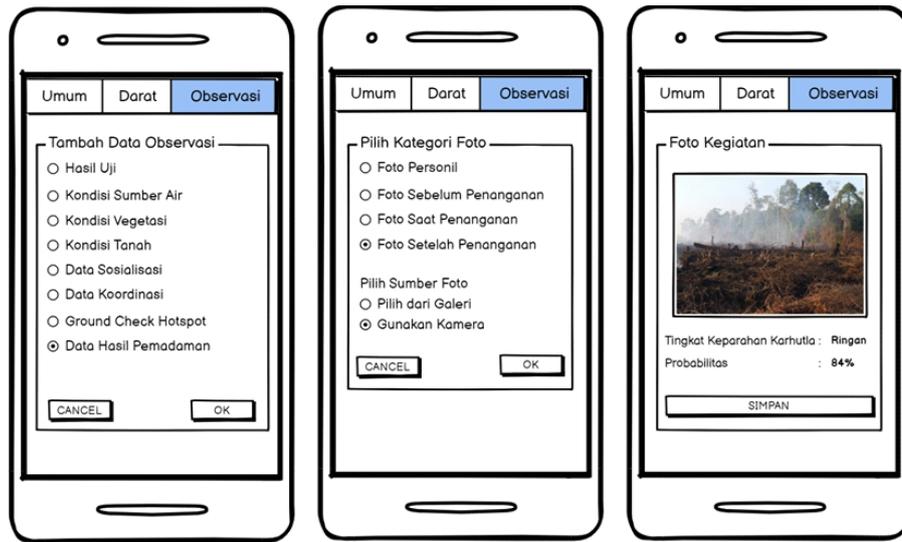


Figure 4 Module interface design.

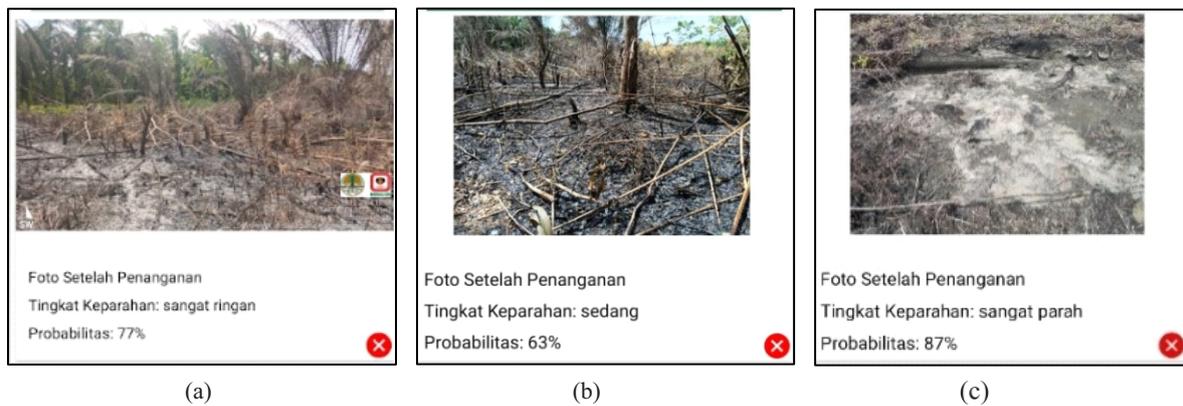


Figure 5 The results of the fire severity module experiment are (a) very low (b) moderate (c) high.

being tested to ensure that the forest fire severity module functions appropriately. The analysis module testing process was conducted in the Manggala Agni Operations Area, Pekanbaru, Riau, on December 9–10, 2024. This testing began with socialization and training for Manggala Agni members regarding using the fire severity module on the SIPP *karhutla* mobile application. The trial was conducted at 3 locations after the forest fire extinguishing in Tapung District, Kampar Regency. The trial was conducted by 10 people who had received training using the fire severity module the previous day. The results of the fire severity module trial on the SIPP *karhutla* mobile application can be seen in Figure 5.

The experiment's results, which were obtained by analyzing several photos of the post-fire extinguishing area, showed excellent results. The analysis shown in Figure 5 shows that the prediction of the severity of forest and land fires varies. In Figure 5(a), the severity is predicted to be low severity, with a probability of 77%. At the same time, in Figure 5(b), the prediction results show a moderate severity with a probability of 63%, and then in Figure 5(c), a prediction of a high severity with a probability of 87%. The predictions produced, including the confidence level, have

followed the standards for assessing the severity of forest and land fires. The image acquisition method has been shown to significantly affect the prediction results and their probability. Optimal image acquisition is done by ensuring that 20% of the image shows the sky while 80% shows the expanse of land. The best time to take pictures is a few days after the fire, and it is also recommended during the day, considering the optimal intensity of sunlight at that time. Bright lighting affects the quality of the resulting image, allowing for image capture with more apparent contrast between burned land and unburned areas. The selection of daytime also reduces the influence of shadows that can affect visual analysis of vegetation and soil conditions after forest and land fires. Image resolution is also an essential consideration in the analysis module. Images with too low a resolution can cause lost details, thus affecting the model's accuracy in identifying severity. Conversely, images with too high a resolution can affect processing time and require greater computing power. The results of testing this module are considered capable of meeting user needs, with several suggestions for improvement in its quality.

Model generalization is also influenced by a number of technical factors. Variations in weather and atmospheric

conditions such as haze, thin clouds, high humidity, and differences in light angles can alter the contrast between burned and unburned areas and lead to prediction bias. Image acquisition quality, such as low resolution, high compression, and differences in equipment (cameras, lenses, and processing pipelines), can potentially obscure important texture details and introduce variations in white balance and noise. Less than ideal shooting composition and geometry, such as sky exceeding 20%, tilted horizons, or inconsistent distances and zooms, can reduce relevant information and alter feature scales compared to the training data. Post-fire capture timing also impacts visual indicators, where capturing too early or too late can alter features such as ash removal or the emergence of new shoots. Regarding label and domain shift, even though labels have been validated by experts, ambiguity in class boundaries is still possible, and the model's generalizability across ecoregions with different soil or vegetation types has not been fully tested. To mitigate these limitations, it is recommended that acquisition protocols include clear daylight, a sky proportion of $\leq 20\%$, optimal angles and distances that highlight the land surface, and the use of the recommended minimum resolution. Periodic validation by experts, expansion of the dataset across regions and seasons, and the application of domain adaptation are important steps to strengthen the model's generalizability in the future.

Discussion

This study develops a forest and land fire severity module using the MobileNetV2 model integrated into the SIPP *karhutla* application. Research related to the development of the SIPP *karhutla* application has been conducted by Sitanggang et al. (2022), which focuses on a forest and land fire prevention system based on mobile and web applications for recording and reporting patrol data in real-time. The system can increase the efficiency of recording and reporting, saving 36.02% in recording time and 56.48% in reporting. Previous research focused on recording all activities in the field, while this study focuses more on handling areas after extinguishing forest and land fires. The analysis module created can provide direct information on the severity of forest and land fires, with accurate and rapid results. This module can provide recommendations for the Ministry of Environment and Forestry in formulating future rehabilitation programs for areas affected by forest and land fires. These two studies certainly contribute significantly to the efforts of the Indonesian Government to control forest and land fires. Previous research plays a vital role in preventing fires by efficiently monitoring and documenting patrol data. At the same time, this study offers a complementary solution, namely a fire severity module, to support more effective recovery actions after forest fires occur. Combining the preventive approach from previous research and the post-fire approach proposed in this study, forest and land fire management in Indonesia can be more comprehensive, from prevention to recovery.

The practical implications of integrating the forest fire severity analysis module into the SIPP *karhutla* mobile application have substantial implications for operational

decision-making in post-fire recovery. First, the integration enables real-time severity classification in the field, allowing Manggala Agni patrol teams to prioritize rehabilitation actions based on the most affected areas. Second, by providing quantitative severity scores with confidence levels, the module supports data-driven allocation. Third, integration with a central database allows policymakers at the Ministry of Environment and Forestry to monitor severity trends over time and across regions, enabling proactive planning for fire prevention and mitigation in high-risk zones.

Conclusion

This study successfully developed a forest fire severity assessment module using the MobileNetV2 model, which has been integrated into the SIPP *karhutla* mobile application. Field testing of the module demonstrated high accuracy in predicting fire severity in post-extinguishing areas, aligning with established assessment standards. The optimal conditions for capturing images were found to be a few days after the fire, preferably during the daytime, when sunlight intensity is at its peak. Additionally, ensuring that 80% of the image captures land while limiting the sky portion to a maximum of 20% significantly improves the prediction accuracy and reliability of severity classification. The module is deemed operationally viable for Manggala Agni, supporting post-fire assessment efforts and aiding in decision-making for rehabilitation strategies in affected areas.

Recommendation

Future development of the analysis module should focus on enhancing its flexibility and adaptability to ensure optimal performance across a wide range of devices, including both low- and high-specification mobile devices. Additionally, the module should be designed for compatibility with multiple hardware platforms and operating systems, allowing for seamless integration and usability across diverse technological environments.

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