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A Smart Decision Support System for Post-Disaster Refugee Repatriation Based on Decision Tree and Facial Emotion Analysis

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Abstract

This study presents a technology-based decision support system to assess the eligibility of post-disaster refugee repatriation, addressing the lack of objective and systematic evaluation tools faced by agencies such as the Batu City Disaster Management Agency. The proposed system integrates a multi-criteria decision tree model with facial expression recognition to evaluate five key factors: disaster status, physical condition of refugees, house condition, surrounding environment, and psychological condition. The decision tree model achieves an accuracy of 92.68%, while the facial expression detection module reaches an accuracy of 73%, with the facial detection process completed in less than 10 seconds. The results demonstrate that this system significantly improves the speed, objectivity, and precision of refugee repatriation evaluations, supporting more effective data-driven recovery strategies. Compared to previous research, the proposed system demonstrates superior outcomes in terms of effectiveness, performance, and efficiency. Unlike earlier approaches that relied on manual assessments without standardized indicators, this system introduces a data-driven mechanism that automates decision-making, reduces processing time, and ensures consistent outputs based on objective and multidimensional criteria.

Keywords : Refugees, BPBD, Information System, Decision Tree, Facial Expression Recognition

1 Introduction

Natural disasters often have significant impacts on communities, including the urgent need for shelter, security guaranties, and a planned recovery process [1]. One of the most crucial challenges in post-disaster management is determining when evacuees can return to their homes safely and appropriately. This process requires a careful evaluation of the environmental conditions and the physical and psychological readiness of individuals. However, in many areas, especially in developing countries, these decisions are often made subjectively and without the support of a standardized assessment system [2].

The phenomenon that occurred in the Batu City Regional Disaster Management Agency (BPBD) illustrates a situation that is relevant to the problem. Following a disaster such as a landslide or flood, BPBD is responsible for determining whether a refugee is eligible to return to their home. Unfortunately, this process still faces various obstacles, especially in triggering nonphysical factors such as psychological trauma [3], [4]. The lack of a smart and organized decision-making system significantly hinders the speed and precision of making decisions.

Most previous studies related to decision support systems in disaster recovery have focused more on assessing physical infrastructure conditions or estimating potential environmental risks [5]. Only a few studies have integrated multidimensional data, especially psychological indicators, into the decision-making process [6]. On the other hand, facial expression recognition technology has developed as a non-invasive method to estimate a person's emotional state and has begun to be intensively applied in the fields of health and human-based computing [7], [8]. However, its application in the context of disaster recovery, especially to assess the feasibility of returning refugees, is rarely explored.

As a contribution to addressing this gap, this study implements a combination of decision tree and facial emotion analysis to support the decision-making process for post-disaster refugee repatriation. The proposed system evaluates five main variables, namely disaster status [9], physical condition, house condition, security of the surrounding environment [10], and psychological conditions analyzed through facial expressions using computer vision [11]. In addition, by integrating with an information system, the decision-making process for the repatriation of refugees can be carried out quickly and precisely, contributing to saving lives and mitigating the impact of disasters on refugees [12], [13].

This study produces several major contributions, namely the development of a multi-criteria model tailored to support objective refugee return decisions and the integration of emotional expression recognition technology into a structured decision-making system. Furthermore, the experimental results show that the decision tree model achieves an accuracy of 92.68%, while the facial expression recognition module reaches an accuracy of 73%. Compared to previous systems, the proposed model demonstrates advantages in terms of effectiveness, performance, and efficiency, offering a more reliable approach to refugee repatriation decision making.

2 Literature Review

In the refugee repatriation process, there are several relevant studies that discuss the importance of considering the determinants of refugee repatriation. Several related studies are as follows: in 2007, the National Commission on Violence Against Women [3] published a case study-based research report on several disasters such as the 2004 tsunami in Ace, the 2005 earthquake in Nias, the 2006 earthquake in Yogyakarta, and the 2006 mudflow disaster in Porong, Sidoarjo. Although its main focus was on the fulfillment of women's human rights in the post-disaster, this report also highlighted the readiness of disaster management institutions in all stages, from the time of the disaster to the post-disaster. The research showed that the process of returning refugees often faced major challenges, such as inadequate housing, limited logistics, and social and psychological problems. Problems such as high sexual access in refugee camps, demands for contract money, trauma to children and women, and inaccurate refugee data complicated the repatriation process. In addition, many refugees experienced psychological disorders such as trauma, anxiety, and prolonged stress.

Research by Michio et al. (2020) [11] on the psychological impact of evacuees from the Fukushima nuclear disaster shows that evacuees who have been repatriated in good health have better psychological conditions than those who are still waiting for clarity on their status. Improper decisions about repatriation can negatively impact the mental health of evacuees. This study also emphasizes the importance of restoring the family's economic condition, because losing a livelihood can hinder the enthusiasm to return to normal life. This aligns with the findings of Beyond Shelter [14], which emphasize that psychological well-being is a key factor in refugee resettlement and recovery, as limited control over housing conditions such as poor quality, location, and accessibility can worsen stress and trauma.

Furthermore, Lee et al. (2022) [15] examined the relationship between time to return home and the physical and mental well-being of refugees. The results showed that refugees with high incomes returned to their activities more quickly because they were able to repair or replace their homes independently. In contrast, low-income refugees depended on government assistance. The condition of the house and the surrounding environment, such as access to the road, water, electricity, and public facilities, also influenced the acceleration of the return process.

Finally, Naomi et al. (2023) [16] studied three cases of evacuees from the Fukushima nuclear disaster and found that many evacuees were reluctant to return because the public facilities of their home areas, especially health services, had not been restored. They chose to stay in the post to get access to care. This study emphasizes the importance of providing health services in their home areas before evacuees are repatriated. In line with this, the study in Zimbabwe [17] highlights that the success of post-disaster repatriation is highly dependent on the participation of multiple sectors. Specifically, the coordinated contribution of medical teams, psychologists and the Regional Disaster Management Agency (BPBD) is crucial to ensure that physical health, psychological readiness, and environmental conditions are properly assessed and addressed. This cross-sector collaboration strengthens the legitimacy and effectiveness of repatriation decisions, ensuring that they are humane, well informed, and aligned with the needs of the affected population.

In making the right decision from various criteria for the repatriation of refugees, an appropriate classification method is needed that can produce high precision. The following are some previous studies related to the decision tree method:

Table 1: Decision tree literature study

No	Reference	Title	Conclusion	Year
1	Ebrahim et al. [18]	Accuracy Assessment of Machine Learning Algorithms Used to Predict Breast Cancer	Predicts the outcome of tumor patients using the decision tree method which produces an accuracy of 98.7%.	2023
2	Nandhini and K.S [19]	Performance Evaluation of Machine Learning Algorithms for Email Spam Detection	Obtained an accuracy of 99.93% for spam email detection.	2020
3	Batitis et al. [20]	Image Classification of Abnormal Red Blood Cells Using Decision Tree Algorithm	Classifying images of abnormal red blood cells resulted in an accuracy of 89.31%.	2020
4	Ramadhan et al. [21]	Comparative Analysis of K-Nearest Neighbor and Decision Tree in Detecting Distributed Denial of Service	Accuracy: KNN = 98.94%, Decision tree = 99.91%.	2020
5	Arowolo et al. [22]	PCA Model For RNA-Seq Malaria Vector Data Classification Using KNN And Decision Tree Algorithm	KNN = 86.7%, Decision tree = 83.3%.	2020
6	Zhang et al. [23]	Prediction of Daily Smoking Behavior Based on Decision Tree Machine Learning Algorithm	Predicts daily smoking behavior with an accuracy of 84.11%.	2019
7	Sathiyanarayanan et al. [24]	Identification of Breast Cancer Using The Decision Tree Algorithm	Achieved 99% accuracy rate in detecting breast cancer.	2019

From Table 1 above, the decision tree method has reliability in classifying the data and its ability to make predictions is one of the viable choices in the decision-making process based on various criteria.

3 Method

3.1 Post-Disaster Refugee Repatriation System Architecture

Based on previous research, a refugee management system has been developed that focuses on the refugee data collection process, as well as several supporting features such as backup features and data reporting. As in Figure 1, the system focuses on the collection of refugee data and only performs health checks as an initial step in identifying refugee conditions. To develop the following research, this study aims to add new features related to the refugee return process. This feature is designed considering various aspects that influence the decision to return, including the status of the disaster, the physical condition of the refugees, the condition of the house and the surrounding environment, and the psychological condition of the refugees.

Based on the system design prepared in Figure 2, the refugee repatriation management process involves various stakeholders according to their respective fields of expertise, to ensure a comprehensive and accurate evaluation [25]. After the refugee data collection process is carried out, the next stage begins with the control and evaluation of the disaster status managed by the Regional Disaster Management Agency (BPBD). Furthermore, the health team will examine the physical condition of the refugees to ensure their suitability for health in the repatriation process. After that, the Quick Response Team (TRC) will evaluate the condition of the house and its surroundings to determine the level of damage and safety of the house. The final stage is a psychological condition check carried out by a team of psychologists to assess the mental readiness of the refugees. In this stage, the psychological assessment process is strengthened by facial detection technology that functions to identify emotional expressions as part of the indicators of the psychological condition of refugees. Although each check is carried out through each system according to the authority and procedures of each team, this entire process remains integrated into one main system that supports cross-sector coordination in an integrated and efficient manner.

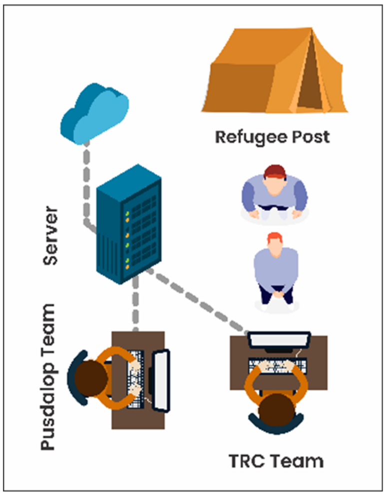

Figure 1: System Design in Previous Research

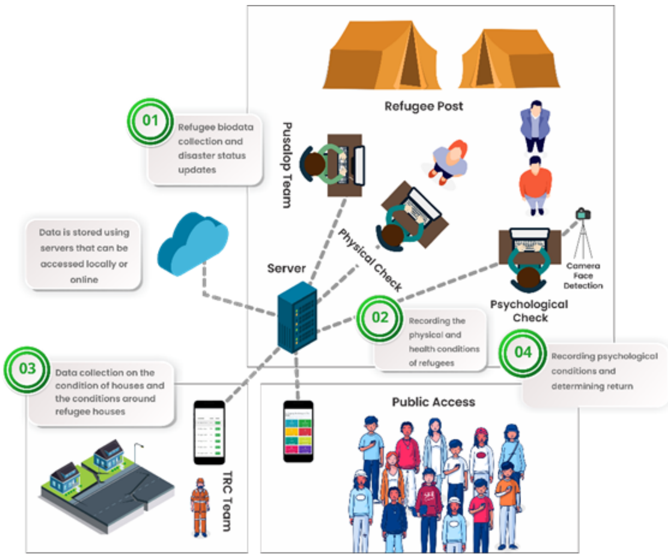

Figure 2: System Implementation Design Plan

3.2 Stakeholder Design and Their Roles

As in Figure 3, in the new feature marked with a red border, there are several main stakeholders who have specific roles in the evaluation and decision-making process. These stakeholders include the Operations Control Center (Pusdalop), the Rapid Reaction Team (TRC), Medical Personnel, and Psychologists. Pusdalop is tasked with monitoring and coordinating all data and the evacuation and return process for refugees. The TRC plays a role in assessing disaster conditions and the physical condition of the homes and surrounding environment of refugees. Medical personnel are responsible for assessing the physical health of refugees, while psychologists focus on examining psychological conditions, including interpreting facial expressions. To support the function of each stakeholder, this system implements a separate account-based authentication mechanism, where each stakeholder has a special login account that provides access according to their role and responsibilities in the system.

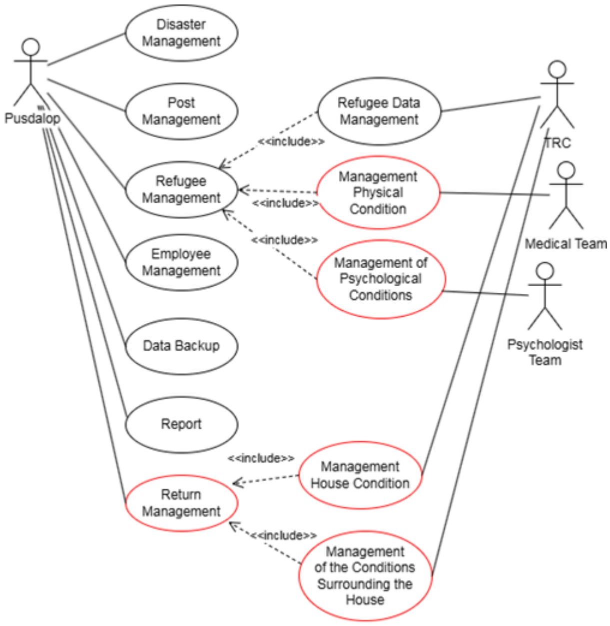

Figure 3: Use Case Diagram Design for System User Stakeholders

3.3 System Flow Chart Design

In the previous system, various important features, such as disaster management, data backup features, reporting, and employee management, have been available that support the overall refugee handling process [3]. To improve the system, in this proposed development, a new feature will be added, namely the refugee return feature, as shown in Figure 4, where the newly added component is marked with a red box.

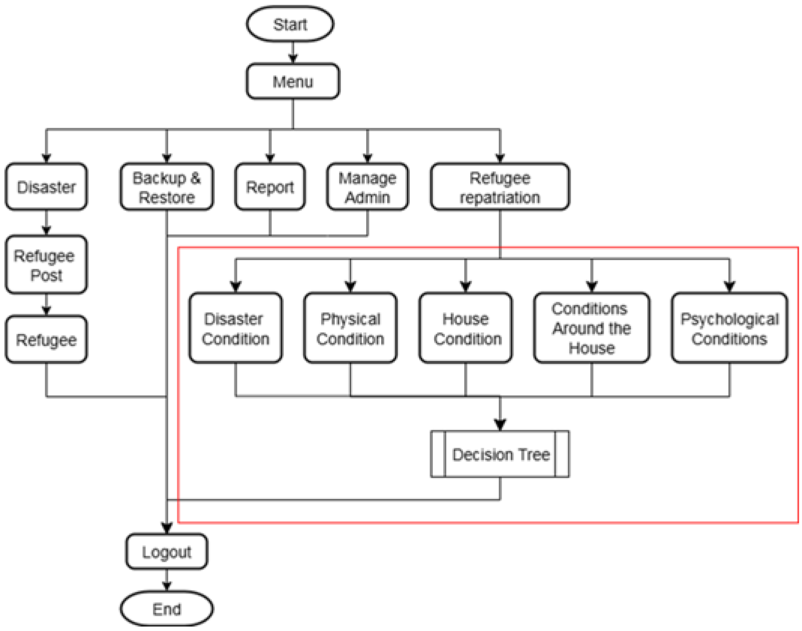

Figure 4: Design addition of features in the system

3.4 Decision Tree Design for Post-Disaster Refugee Repatriation Decision System

In general, this method relies on the basic principles of binary logic, namely the values 0 and 1 [26]. These values represent two different categories, which can be adjusted to the context of the problem, such as the classification of "yes" or "no", "true" or "false", or "positive" and "negative". In the decision-making process, each branch applies these binary rules to evaluate specific indicators that form the basis of the decision. The detailed definition of these indicators is described in Table 2, which presents the criteria used to determine refugee repatriation eligibility, including detailed descriptions, assigned weights, and specific provisions. These criteria encompass disaster status, physical health condition, house condition, surrounding environment condition, psychological condition scores from six questions, and results of facial expression analysis. Each of these criteria serves as the foundation for the decision-making process within the system.

Based on Table 2, the process begins with evaluating the status of the disaster. If the disaster is in the recovery phase, the system is able to assess the physical condition of the refugee. A physically healthy or mildly injured state leads to the next assessment of the condition of the house and the surrounding environment. If these are deemed safe, lightly damaged, or moderately damaged, the system continues with the final evaluation of psychological condition and facial expression. Only when all conditions are satisfied will the refugee be classified as eligible for repatriation. This flowchart bridges the conceptual criteria in Table 2 with the implementation logic applied in the system.

The decision tree model, as shown in Figure 5, is then constructed on the basis of these criteria and flow logic. This model operates by recursively splitting the data set according to the most influential attributes, where each internal node represents a test on an attribute, each branch corresponds to the result of that test, and each leaf node represents the final decision ("Permitted to Return" or "Not Yet Permitted to Return"). For example, the tree begins with totalPsiko (the score obtained from the results of the psychological tests), followed by attributes such as konFis (physical condition), statBen (disaster status), and konMah (house condition), leading to the final decision. Other relevant indicators also include konSekRum (home conditions), which further strengthen the decision-making process. The numerical values in the figure (e.g. $<$ 12,500; $>$ 2,500; $>$ 1,500) represent the weighted thresholds assigned to each attribute, as presented in Table 2, indicating their relative influence on the classification results. Although the tree structure serves as a data-driven prioritization guide, in practical implementation, it is adapted to align with institutional policies and real-time conditions in the field.

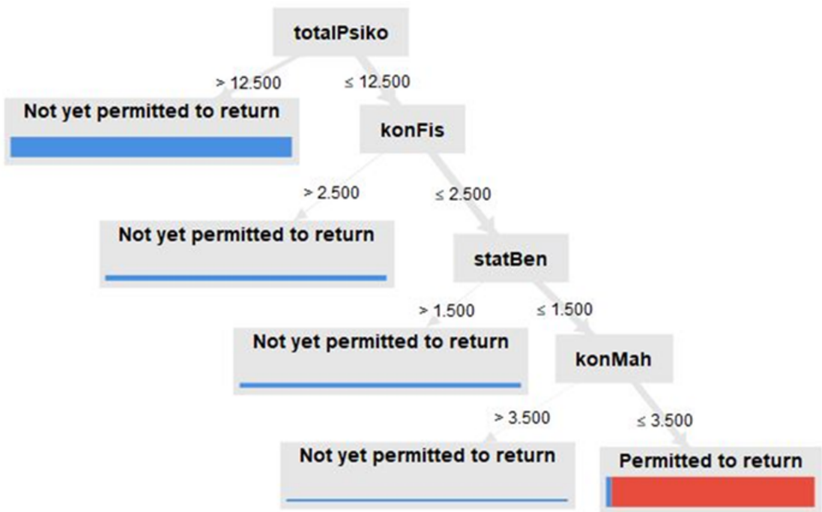

Figure 5: The research decision tree structure

Table 2: Criteria for Refugee Return Decision

No.	Criteria	Details	Explanation	Weight of Value	Provision
1	Disaster status (Can be updated within 2x24 hours) [9]	Recovery	Disaster threat has subsided/ended	1	Refugees may return home if the disaster situation is in recovery status.
		Emergency response	Disaster threats occurring	2	
		Emergency alert	The potential threat of disaster	3	
2	Physical health condition (Can be recorded within 2x24 hours) [10]	Healthy		1	Refugees may return home if they have minor injuries or are in good physical condition.
		Minor injuries	Outpatient	2	
		Serious injuries	Hospitalization	3	
		Deceased		4	
		Missing		5	
3	House condition (Can be recorded periodically) [10]	Safe		1	Refugees may return home if their homes are safe, and have only minor or moderate damage.
		Slightly damaged	Habitable but needs repair	2	
		Moderately damaged	Habitable and damaged	3	
		Heavily damaged	Uninhabitable	4	
4	Conditions around the house (Can be recorded periodically) [10]	Safe		1	Refugees may return home if the conditions around their homes are safe, there is only minor or moderate damage.
		Slightly damaged		2	
		Moderately damaged		3	
		Heavily damaged		4	

No.	Criteria	Details	Explanation	Weight of Value	Provision
5	Psychological condition (Can be done on the 7th day or can be accelerated according to conditions) [16], [27], [28]	Question 1	Since being at the post, how often have you been nervous?	0-4	Refugees may return home if the accumulated points from 6 questions are less than 13 points Weight 0 is worth never Weight 1 is worth a little Weight 2 is worth a few times Weight 3 is worth often Weight 4 is worth always
		Question 2	Since being at the post, how often have you felt hopeless?	0-4	
		Question 3	Since being at the post, how often have you been anxious?	0-4	
		Question 4	Since being at the post, how often have you been depressed?	0-4	
		Question 5	Since being at the post, how often have you experienced difficult things?	0-4	
		Question 6	Since being at the post, how often have you felt worthless?	0-4	
6	The facial expression recognition process is carried out while refugees are answering psychological questions [29]	Angry Expression		0	Refugees can be allowed to return home if the refugee's expression is happy or neutral.
		Happy Expression		1	
		Neutral Expression		2	
		Sad Expression		3	
		Surprized Expression		4	

3.5 Facial Expression Recognition

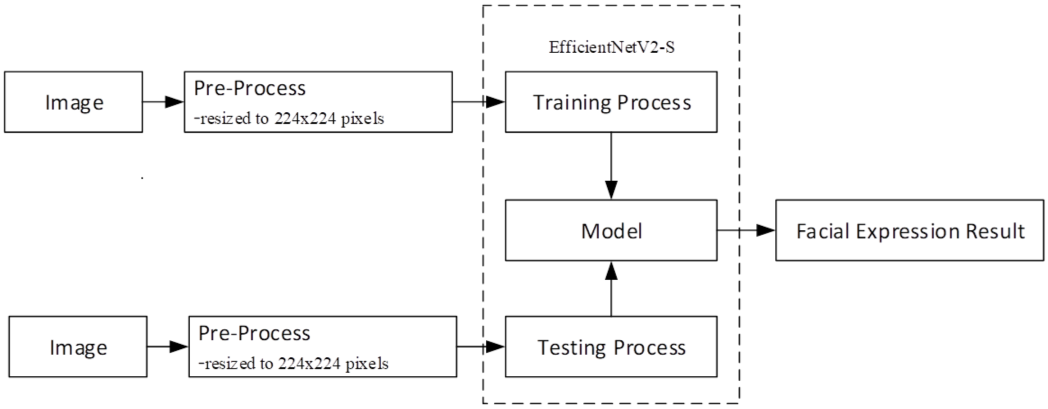

Figure 6: The architecture of EfficientNetV2-S

As illustrated in Figure 6, the first step in the facial expression recognition process is to gather facial image data that have been categorized according to expressions such as happy, neutral, angry, scared, disgusted, and sad. The data set must contain a sufficiently representative number of data for each class, with a minimum of 1,000 images per class. The images were sourced from public datasets: FER2013 and RAF-DB. Subsequent to data collection, a preprocessing phase was executed to guaranty consistency of the input provided to the model. Every image is resized to 224x224 pixels to comply with the input requirements of EfficientNetV2. The pixel values of the images are standardized to the interval [0,1]. To enhance data diversity and prevent overfitting, techniques for data augmentation, including random rotation, cropping, zooming, horizontal flipping, and modifications to contrast and brightness, are employed.

The unequal class distribution in the dataset can impact the model's efficacy; therefore, data balancing is implemented to achieve an equitable number of images per class. This is done to prevent oversampling or undersampling. Upon achieving balance, with each class containing 1,200 images, the overall dataset is rendered more uniform and prepared for partitioning into training and validation sets. A balance process was conducted to rectify this imbalance, as illustrated in Figure 7.

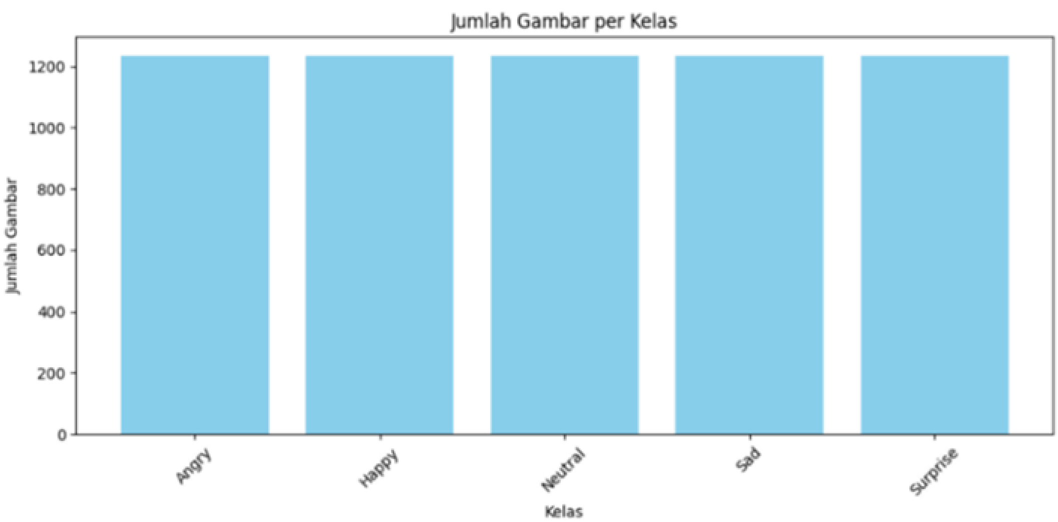

Figure 7: Balancing process on dataset

The prepared data set is divided into two subsets, namely training data (train) and validation data (validation), with a general proportion of 80:20. For example, of 7,200 available images, 5,760 are used for training and 1,440 for validation. This division is done randomly, but stratified, that is, ensuring that the proportion of classes remains balanced in both subsets. The model is trained using the training data, while the validation data is used to measure its performance on data it has not encountered before [30].

In Figure 8, the graphs show the accuracy of the model and the progression of loss over nine epochs for the training (train), validation (val) and testing (test) datasets. In the accuracy graph, the training accuracy (blue) starts at around 50% steadily increases to approximately 83% by the last epoch. Validation accuracy (orange) begins at about 66% quickly rises to around 75% by the third epoch, and peaks at roughly 79% before slightly declining, suggesting mild overfitting after the seventh epoch. The test accuracy (green) follows a trend similar to the validation accuracy, starting near 66% and stabilizing between 72–76% showing a consistent generalization to unseen data. In the loss graph, the training loss decreases sharply from about 1.45 to 0.45, indicating effective learning. Validation and test losses also drop significantly in the early epochs and then stabilize, with slight fluctuations, which may reflect the model adapting to data variability. Overall, the model learns well, but the divergence in training and validation accuracy after several epochs signals the need for overfitting prevention measures.

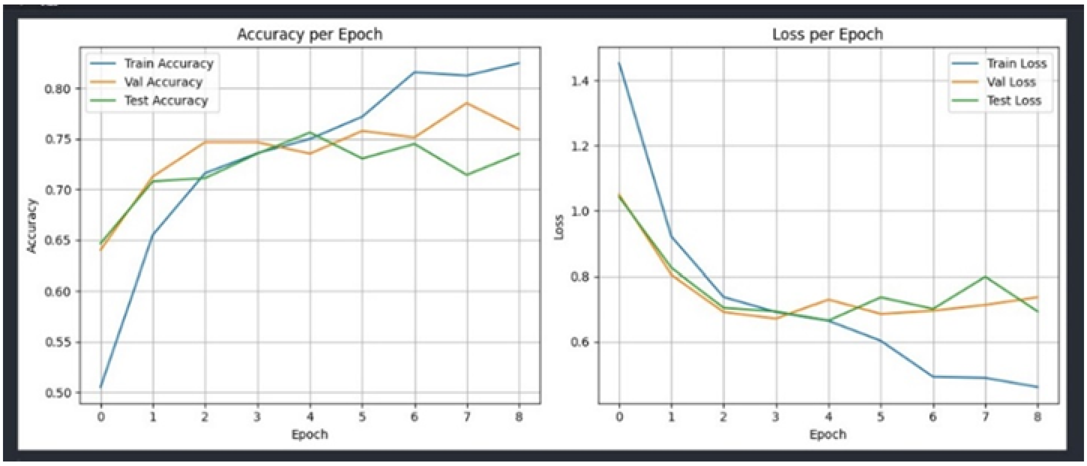

Figure 8: Dataset checking process

Meanwhile, in Figure 9 below, the confusion matrix shows the model's performance in classifying five types of facial expressions: angry, happy, neutral, sad, and surprised. Each row represents the actual label, while each column indicates the label predicted by the model. From this matrix, it can be seen that the model performs fairly well in recognizing happy and surprise expressions, indicated by the high number of correct predictions of 217 and 236, respectively. However, for expressions such as neutral and sad, the model still experiences confusion with other expressions, especially seen from the many neutral predictions that are incorrectly classified as sad (41 cases) and vise versa (64 cases). This shows that although the model is generally able to classify with good accuracy, there is still room for improvement in distinguishing expressions that have similar visual characteristics, especially between neutral and sad. This model is integrated into the refugee information system, especially in the psychological evaluation section [31].

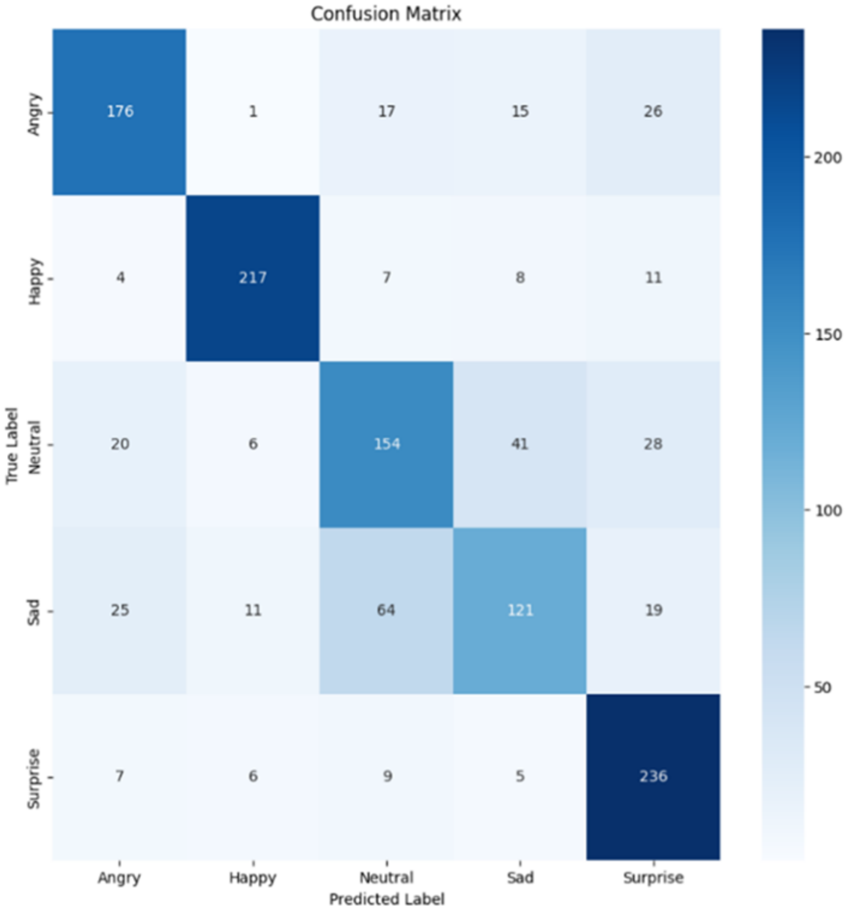

Figure 9: Confusion matrix in model

4 Result And Discussion

In this chapter, two main focuses of testing are discussed, namely facial expression recognition testing and integration testing between multi-criteria decision trees and the facial expression recognition process. Each test is evaluated by examining its precision, system performance, and alignment with the main goals of the system, allowing this chapter to present a detailed assessment of the reliability and effectiveness of the system.

4.1 Facial Expression Recognition Testing

In the testing process, the website is connected to an API that leads directly to the facial expression recognition application, so that it can send image data and receive facial expression analysis results in real-time. In the testing process, the user inputs a face to be detected and the system will display the identified facial expression along with a confidence score, which represents the system's level of certainty that the detected expression is correct [32].

Table 3: Facial expression recognition testing

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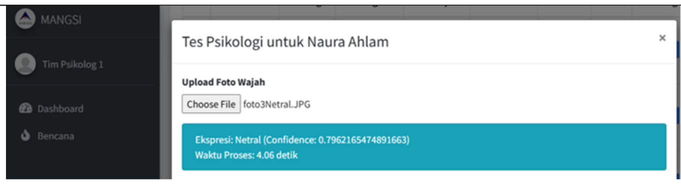
<tr><th>No.</th><th>Detected Foto</th><th>Detected Result</th></tr>
<tr><td>1</td><td></td><td>
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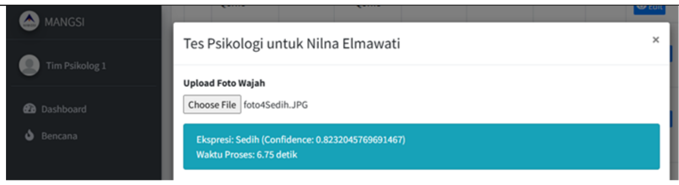
<tr><td>2</td><td></td><td>
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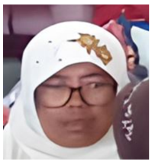
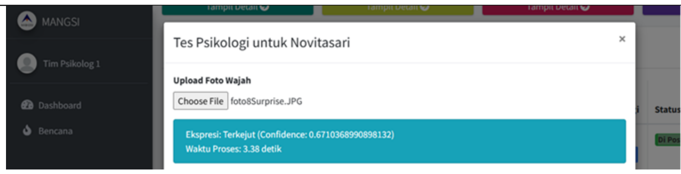
<tr><td>3</td><td></td><td>
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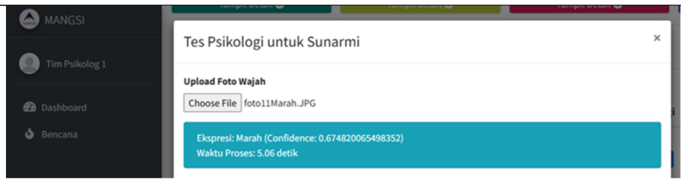
<tr><td>4</td><td></td><td>
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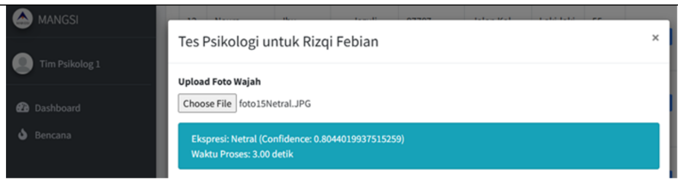
<tr><td>5</td><td></td><td>
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Based on the results of facial expression testing in Table 3, it can be concluded that the confidence level generated by the system falls into a good and appropriate category. The system is able to detect expressions with confidence values that generally reach above 70% depending on image resolution and lighting conditions.

4.2 Integration Testing of Decision Tree Method and Facial Expression Recognition

The decision tree model testing in this study utilized a data set that contains important attributes related to refugees. The data set includes information such as refugee identification, results (labels indicating eligibility to return), statBen (disaster status), konFis (physical condition), konMah (house condition), konSekRum (conditions around the house) and totalPsiko (the score obtained from the results of psychological tests). In the design process, the Decision Tree method testing was carried out through two main flows, namely the training process and the testing process. After applying undersampling, the data set was divided into 152 training records and 41 testing records. During the training stage, the data was first loaded using the retrieve operator containing the data set, then missing values were handled through Replace Missing Values, followed by the selection of important attributes using Select Attributes before the Decision Tree model was built. An example of the data set used can be seen in Figure 10.

Row No.	results	statBen	konFis	konMah	konSekRum	totalPsiko
139	Permitted to return	1	2	1	2	1
140	Permitted to return	1	1	1	3	7
141	Permitted to return	1	2	3	3	0
142	Permitted to return	1	1	2	3	8
143	Permitted to return	1	2	3	3	7

Figure 10: Dataset used in decision tree testing

Meanwhile, in the testing process, the test data are loaded with a retrieve containing a dataset containing 15 data, processed in the same way as the training data to ensure consistency, and then applied to the model using the Apply Model. The prediction results are compared with the actual labels using the Performance operator, which provides an evaluation in the form of precision, precision, recall metrics, and confusion matrix visualization as in Table 4.

Table 4: Decision Tree Test Results

	True not yet permitted to return	True permitted to return	Class precision
Pred. not yet permitted to return	18	0	100%
Pred. permitted to return	3	20	86.96%
Class recall	85.71%	100%	
Accuracy	92.68%		

The results of the Decision Tree model test for the prediction of refugee repatriation status are presented in Table 4. Based on the confusion matrix, the model demonstrates good performance in classifying both classes, namely Not Yet Permitted to Return and Permitted to Return. Of the 18 instances truly categorized as not yet permitted to return, all were correctly classified (precision 100% although three misclassifications occurred where the model incorrectly predicted the status as allowed to return. On the other hand, the Permitted to Return class achieved a perfect recall of 100% despite a slightly lower precision of 86.96%Ȯverall, the model reached an accuracy of 92.68% indicating that the Decision Tree is highly effective in predicting refugee repatriation status based on the selected features. Evaluation metrics such as recall, precision, and F1-score further support these findings, though it should be emphasized that the conclusions are drawn from a relatively small dataset and therefore require further validation to ensure generalizability. To complement this, system-level tests were also carried out by inputting data into the application to verify its functionality, the results summarized in Table 5. The tests were conducted on a laptop equipped with 8GB of RAM and an AMD A8 processor, which represents typical mid-range hardware specifications.

Based on Table 5, there are several column titles used as references, such as idPeng (refugee id), statBen (disaster status), konFis (physical condition), konRum (house condition), konSek (surrounding condition), psiko (accumulation of psychological scores) and expression (facial expression detection results). From the table, the system has been proven to be able to detect and provide well-defined decisions on the eligibility of repatriating refugees based on a number of predetermined criteria. In addition, the facial expression detection process for each individual was completed in less than 10 seconds, adjusted according to the server's hardware specifications.

4.3 Comparison with Previous Studies

To evaluate the success of the proposed system, a comparison was conducted with previous studies based on indicators of effectiveness, performance, and efficiency. These three indicators are relevant benchmarks for system evaluation [33], as commonly applied in the 3E model and the Balanced Scorecard framework [34].

Table 5: Refugee repatriation decision

No.	idPeng	stat Ben	konFis	kon Mah	konSek	psiko	expression	Processing time (s)	Results	Details
1	P1	Disaster alert	Minor Injuries	Safe	Safe	0	Neutral	9.67	Not yet permitted to return	Not yet permitted to return due to disaster alert status
2	P2	Emergency response	Healthy	Safe	Safe	9	Happy	8.07	Not yet permitted to return	Not yet permitted to return due to disaster status
3	P3	Recovery	Serious Injury	Minor damage	Moderate damage	10	Neutral	8.84	Not yet permitted to return	Not yet permitted to return due to serious physical injuries
4	P4	Recovery	Health	Severely damaged	Safe	12	Neutral	6.18	Not yet permitted to return	Not yet permitted to return because the house is badly damaged
5	P5	Recovery	Health	Safe	Severely damaged	8	Happy	4.31	Not yet permitted to return	Not yet permitted to return because the surrounding conditions are badly damaged
6	P6	Recovery	Health	Safe	Safe	15	Neutral	8.76	Not yet permitted to return	Not yet permitted to return because the psychological condition score exceeds 15 points
7	P7	Recovery	Health	Safe	Safe	12	Sad	5.60	Not yet permitted to return	Not yet permitted to return because the detected expression result is sad
8	P8	Recovery	Minor Injuries	Safe	Minor Damage	3	Neutral	6.77	Permitted to return	Permitted to return home
9	P9	Recovery	Health	Safe	Safe	10	Happy	4.37	Permitted to return	Permitted to return home

This analysis aims to highlight the advantages of the proposed system in addressing the limitations of previous approaches, which often lacked measurable evaluation indicators.

4.3.1 System Effectiveness

The effectiveness of the system is evaluated by comparing the outcomes of the decisions generated by the system in terms of the precision of the decision, the decision criteria, and the consistency of the output.

Based on the testing results in Table 6, the proposed system has proven to be more effective than previous approaches. By incorporating objective indicators such as disaster status, housing condition, physical and psychological health, and facial expression detection, the system provides more accurate and consistent decisions. The integration of decision tree and facial expression detection methods significantly enhances the system's effectiveness in determining the eligibility for post-disaster refugee repatriation.

4.3.2 System Performance

To evaluate the advantages of the proposed system, performance testing was conducted by comparing it with previous research. Performance aspects tested include data processing speed, facial expression detection time, and system stability when handling various input combinations. This evaluation aims to determine the extent to which the new system can operate optimally and efficiently to deliver accurate results within a short time frame. The processing time of the current study is presented in Table 7.

Table 6: Comparison results of system effectiveness testing

No.	Aspect of effectiveness	Previous research	Current research
1	Decision accuracy	No system testing was conducted; refugee repatriation decisions were made manually	Decisions are generated through facial expression detection and decision tree classification with 92.68% accuracy
2	Decision criteria	Only considered physical data and housing conditions, without psychological aspects	Utilizes five criteria: disaster status, physical condition, housing, environment, and facial expression
3	Output consistency	No systematic data available; decisions were mostly subjective	The system produces automatic and consistent decisions for similar inputs

Table 7: System Response Time

No.	Refugee Repatriation Process Flow	System Time
1	Disaster status verification in the system	5 seconds
2	Refugee data entry by the Rapid Response Team (TRC)	5 minutes
3	Physical condition assessment by the medical team	3 minutes
4	Housing condition assessment by the TRC	2 minutes
5	Surrounding environment assessment by the TRC	2 minutes
6	Psychological condition assessment by the psychology team	3 minutes
7	Display of repatriation decision results	Realtime
Total time required by the system to process one complete data input		15 minutes 5 seconds

Based on the system testing results, the time required to fully process a single data entry across all indicators including disaster status, physical condition, housing condition, surrounding environment, psychological condition, and facial expression detection is 15 minutes and 5 seconds. This duration covers all stages, from data input and processing through the decision tree system to the final output of the refugee repatriation recommendation. The measured duration reflects the actual operational time required, including facial expression detection and input data validation. Detailed performance measurements are presented in Table 8.

The developed system demonstrates superior performance compared to previous studies. In contrast to earlier methods that relied on manual assessments and lacked standardized time frames, the current approach enables objective decision-making within approximately 15 minutes and 5 seconds, incorporating facial expression detection that takes less than 10 seconds per individual. Using a local XAMPP server and MySQL database, the system operates efficiently without the need for a sophisticated infrastructure, thus improving its effectiveness in facilitating refugee repatriation decisions.

4.3.3 System Efficiency

To evaluate the efficiency level of the system, a comparison was conducted between the previous study and the proposed system focusing on three main indicators: degree of process automation, system availability, and time savings in decision-making. This approach enables the assessment of how far the proposed system improves efficiency compared to the manual approach used in previous research. The results of the system efficiency testing are presented in Table 9.

Based on the analysis of three main efficiency indicators that are process automation, system availability, and time savings, the system proposed in this study is more efficient than the previous research. It is capable of operating automatically, is easily accessible through a local server, and produces decisions more quickly. In contrast, previous approaches relied on manual processes that were time-consuming and required additional effort.

Table 8: Comparison Results of System Performance Testing

No.	Performance Aspect	Previous Research	Current Research
1	Decision Time	Not available; the decision-making process was performed manually by officers based on physical and environmental observations	Approximately 15 minutes and 5 seconds per individual using an automated local classification system
2	Facial Expression Detection Time	Not available; facial expression was not included as an evaluation parameter	Less than 10 seconds per face, enabling near real-time detection depending on hardware performance
3	System Requirements	No digital system implementation; procedures were conducted using conventional manual methods	Implementation of a local server environment (XAMPP), browser-based interface (localhost:8080), and MySQL database for data management

Table 9: Comparison Results of System Efficiency

No.	Efficiency Aspect	Previous Research	Current Research
1	Automation	Decision-making and evaluation were performed manually by field teams	The system processes input data automatically and generates output without additional intervention
2	System Availability	No application system was available	The system can be accessed and tested locally through a web-based interface
3	Time Efficiency	The decision-making process lacked a definite time frame	The total process from input to decision takes approximately 15 minutes and 5 seconds per data entry

4.4 System Feasibility Analysis

In the testing process, it is necessary to evaluate the implementation of the system, particularly the integration of the decision tree method and facial expression detection, to ensure its effective application in real-world contexts. During implementation, several limitations were identified that require careful consideration.

4.4.1 Refugee Dataset Limitations

Based on research and exploration conducted on various open-source dataset platforms such as Kaggle, the UCI Machine Learning Repository, and the official websites of humanitarian and disaster-related organizations, it was found that the availability of refugee datasets with specific return-related indicators such as disaster status, physical condition, housing condition, environmental surroundings, and psychological status is still highly limited. Most publicly available datasets only include general information such as the number of refugees, evacuation locations, and types of disasters, without accommodating the more complex and multidimensional indicators required by the proposed system. This limitation poses a significant challenge in the development and training of the decision tree model, as an effective model requires representative and diverse data. Therefore, in this study, part of the data set was manually constructed and simulated based on scientific references and relevant case studies to ensure that the system could still be functionally tested. As a result, the data set included a total of 204 processed data entries. In the future, it is crucial for relevant institutions to develop a more comprehensive and standardized refugee database to support the development of more accurate and applicable decision support systems.

4.4.2 Challenges in Real-Time Facial Expression Detection

Real-time facial expression detection poses a major challenge in the implementation of the proposed system. This process requires intensive image processing and is highly sensitive to several factors, including lighting quality, facial positioning, and camera resolution. When running on devices with low specifications, the system tends to experience delays (lag) in accurately and promptly recognizing facial expressions. These limitations highlight the need for high-performance servers or computing devices, both in terms of processing speed (CPU/GPU) and operating system stability, to ensure effective real-time detection. As part of the system evaluation, the researcher conducted tests using an alternative device with higher specifications, including a faster processor, a larger RAM capacity, and a high-resolution camera with optimal lighting conditions. The results showed a significant improvement in detection speed and facial expression recognition accuracy. The comparative process of validating facial expression detection is presented in Figures 11 and Figure 12.

Figure 11 illustrates that the facial detection process operates with a confidence score of 0.98 and a processing time of approximately 1 second per expression change. Meanwhile, in Figure 12, the facial detection process exhibits a slower detection time, requiring approximately ±14 seconds for each expression change, with a confidence level of 0.49. The differences in the device specifications used can be observed in Table 10.

The difference in device specifications significantly affects the performance of real-time facial detection processes. On high-specification devices such as the Ryzen 5 5600H, RTX 3050 4GB GPU, and 40GB RAM, the system is capable of running detection processes quickly, responsively, and with minimal interference even under varying lighting conditions. In contrast, on devices with lower-specification such as the AMD A8-7410 with Radeon R5 and 8GB RAM, the detection process is slower, often experiences lag, and the accuracy of facial expression tends to decrease due to limited processing and graphics capabilities. This indicates that real-time facial detection is highly dependent on hardware support, particularly in ensuring smoothness, speed, and accuracy when deploying the system in real-world settings.

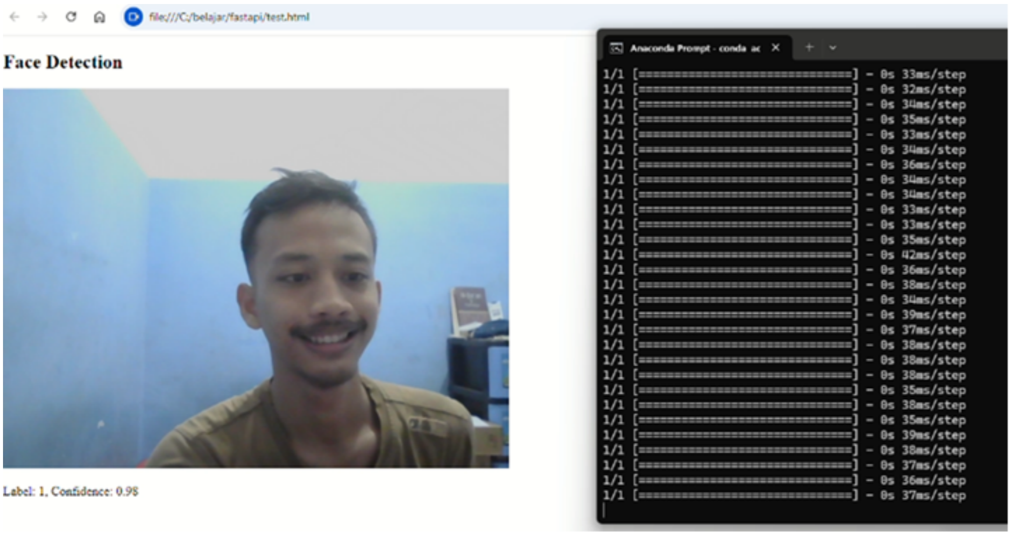

Figure 11: system with faster facial detection

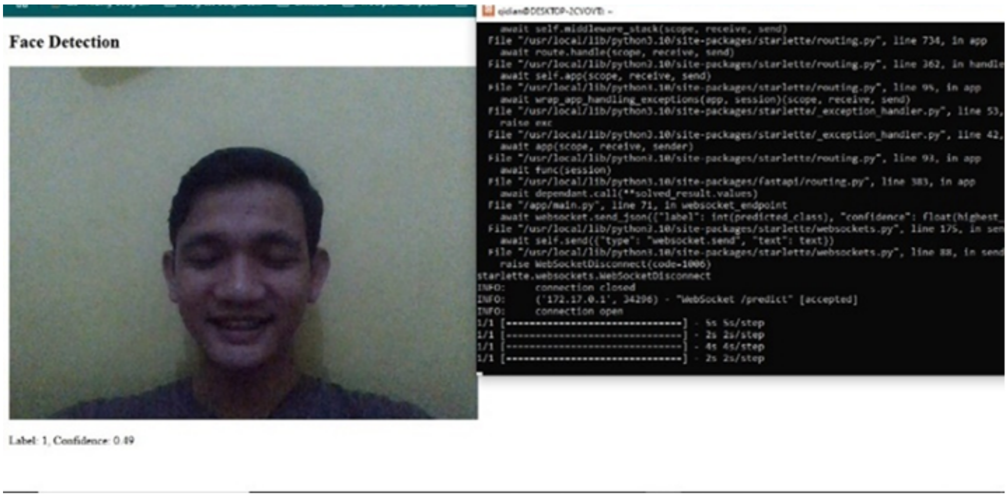

Figure 12: The process of facial detection in this research

Table 10: Comparison of Research Device Specifications

No.	Indicator	Device Specifications in Figure 12	Device Specifications in Figure 13
1	Processor	Ryzen 5 5600H	AMD A8-7410 APU
2	GPU	RTX 3050 4GB	AMD Radeon R5
3	RAM	40GB	8GB

5 Conclusion

Based on design and testing results, it can be concluded that the smart decision support system for post-disaster refugee repatriation based on decision tree and facial emotion analysis can function as expected. This system can assist BPBD officers in determining the eligibility of refugees to return to their homes by considering various important variables, namely disaster status, physical condition of refugees, house conditions, environmental conditions around the house, and psychological conditions of refugees. The decision-making process is carried out using a decision tree algorithm, which in the initial tests achieved an accuracy of 92.68%, indicating its potential to effectively generalize the decision rules. In addition, the facial expression detection feature also works well, reaching an accuracy of 73% with an average processing time of less than 10 seconds, demonstrating that the system is capable of supporting the analysis of the psychological conditions of refugees.

Furthermore, integration of this system provides added value by improving the existing refugee management system with a new feature of repatriation eligibility. Previously, the system only covered basic refugee registration, shelter assignment, and health check processes. With the inclusion of this decision support feature, the system now offers a more comprehensive approach by not only recording data, but also aiding in crucial decision-making processes.

Compared to previous research, the proposed system demonstrates superior outcomes in terms of effectiveness, performance, and efficiency. Unlike earlier approaches that relied on manual assessments without standardized indicators, this system introduces a data-driven mechanism that automates decision-making, reduces processing time, and ensures consistent outputs based on objective and multidimensional criteria. However, several limitations must be acknowledged. The system evaluation was conducted on a limited dataset, which may not fully represent the diversity of real-world scenarios. Although the model demonstrated favorable performance during testing, further validation is required using larger and more diverse datasets, supported by techniques such as cross-validation. Additionally, the facial emotion detection process depends heavily on image quality and lighting conditions, which may affect accuracy in real-world implementations. In future research, it is also important to consider that devices with higher hardware specifications—such as faster processors, greater memory capacity, and higher-resolution cameras—can significantly enhance the reliability, responsiveness, and accuracy of real-time facial expression detection.

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