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DEEP LEARNING APPROACH FOR RECOGNIZING SUBSIDIZED GAS RECIPIENTS USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract— *Inaccurate targeting in subsidized LPG distribution remains a persistent policy challenge in Indonesia, where manual verification processes are vulnerable to misuse and administrative error. Addressing this gap, the present study develops and evaluates a biometric identity verification system based on Convolutional Neural Networks (CNNs) to improve the accuracy and accountability of subsidy allocation at the point of distribution. Following the CRISP-DM framework, two CNN architectures with fundamentally different design philosophies were compared: ResNet-IR, optimized for representational depth and recognition accuracy, and MobileFaceNet, designed for computational efficiency on resource-constrained hardware. Both models were sourced from the InsightFace framework as pre-trained models and evaluated on a locally acquired dataset of 111 registered subsidy recipients from Pajang Village, Tangerang City. Evaluation across face identification (1:N) and face verification (1:1) tasks reveals that ResNet-IR consistently outperforms MobileFaceNet, achieving an accuracy of 94.7% with a precision, recall, and F1-score of 0.9043, compared to MobileFaceNet's accuracy of 93.7% and F1-score of 0.8862. The primary contribution of this work is to demonstrate, for the first time in the Indonesian subsidy distribution context, that deep learning-based facial recognition can serve as a viable, deployable mechanism for biometric identity verification in public service programs offering a technically grounded pathway toward more transparent and equitable subsidy targeting.*

Keywords: *Biometrics, Convolutional Neural Network (CNN), Facial Recognition, Identity Verification, MobileFaceNet*

Intisari— *Penargetan yang tidak akurat dalam distribusi LPG bersubsidi tetap menjadi tantangan kebijakan yang kronis di Indonesia, di mana proses verifikasi manual rentan terhadap penyalahgunaan dan kesalahan administratif. Untuk mengatasi kesenjangan ini, penelitian ini mengembangkan dan mengevaluasi sistem verifikasi identitas biometrik berbasis Convolutional Neural Networks (CNN) guna meningkatkan akurasi dan akuntabilitas alokasi subsidi pada titik distribusi. Mengikuti kerangka kerja CRISP-DM, dua arsitektur CNN dengan filosofi desain yang secara fundamental berbeda dibandingkan: ResNet-IR, yang dioptimalkan untuk kedalaman representasi dan akurasi pengenalan, serta MobileFaceNet, yang dirancang untuk efisiensi komputasi pada perangkat keras dengan keterbatasan sumber daya. Kedua model diperoleh dari kerangka kerja InsightFace sebagai model pra-terlatih dan dievaluasi pada dataset yang diperoleh secara lokal dari 111 penerima subsidi terdaftar di Desa Pajang, Kota Tangerang. Evaluasi terhadap tugas identifikasi wajah (1:N) dan verifikasi wajah (1:1) menunjukkan bahwa ResNet-IR secara konsisten mengungguli MobileFaceNet, mencapai akurasi 94,7% dengan nilai presisi, recall, dan F1-score sebesar 0,9043, dibandingkan dengan akurasi MobileFaceNet sebesar 93,7% dan F1-score sebesar 0,8862. Kontribusi utama dari penelitian ini adalah menunjukkan, untuk pertama kalinya dalam konteks distribusi subsidi Indonesia, bahwa pengenalan wajah berbasis deep learning dapat berfungsi sebagai mekanisme verifikasi identitas biometrik yang layak*

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dan dapat diimplementasikan dalam program pelayanan publik menawarkan jalur yang berbasis teknis menuju penargetan subsidi yang lebih transparan dan berkeadilan.

***Kata Kunci**: Biometrik, Convolutional Neural Network (CNN), Pengenalan Wajah, Verifikasi Identitas, MobileFaceNet*

INTRODUCTION

The distribution of subsidized 3-kilogram LPG cylinders is one of Indonesia's most critical social protection instruments, designed to ensure affordable energy access for low-income households, small businesses, and other vulnerable groups [1], [2]. However, the program has long struggled with systemic inefficiencies: subsidized gas frequently reaches ineligible recipients while registered beneficiaries face recurring shortages, undermining both the program's fiscal integrity and its social objectives [3]. At the core of this problem lies a verification gap — distribution agents currently rely on manual identity checks that are easily circumvented, leaving the program exposed to misuse and leakage. Addressing this gap requires an automated, reliable identification mechanism capable of operating in real-world field conditions. The application of deep learning and computer vision techniques offers a technically grounded pathway toward this goal [4], with facial recognition emerging as a particularly promising approach for non-intrusive, real-time identity verification at distribution points [5], [6], [7].

The foundational relevance of deep learning to this problem is well-documented. Li [8] (2022) conducted a comprehensive review of deep learning applications in image recognition, demonstrating that Convolutional Neural Networks (CNNs) consistently outperform earlier approaches across a range of visual identification tasks. By systematically comparing CNN, RNN, and GAN architectures, the study establishes CNNs as the dominant paradigm for feature extraction in facial recognition, medical imaging, and remote sensing classification. Crucially, the study identifies model robustness and real-time inference as the two primary frontiers for future development — both of which are directly relevant to the deployment context of this research.

The capacity of ResNet-based architectures to deliver high accuracy on constrained local datasets has been demonstrated beyond the facial recognition domain. Cynthia et al. [9] (2022) developed a cloud-type classification system using the Faster R-CNN framework with ResNet-IR feature extraction, applied to the CCSN dataset comprising 626 images across three cloud categories. The approach achieved an accuracy of 94.12% with an average precision of 0.76, overcoming the computational limitations of selective search algorithms while maintaining stable training convergence. This result is significant for the present study because it confirms that ResNet-IR can generalize effectively to small, domain-specific datasets — a characteristic directly applicable to the limited local dataset of LPG subsidy recipients used here.

The broader applicability of biometric systems to government service delivery has been empirically validated in the Indonesian institutional context. Sidik et al. [10] (2024) developed an IoT and web-based biometric attendance system integrating fingerprint sensors, NodeMCU ESP8266 for wireless transmission, and a PHP-MySQL monitoring dashboard, deployed and tested at SMPN 31 Tangerang. The system demonstrably reduced attendance manipulation and improved administrative efficiency relative to conventional manual methods. Beyond its immediate findings, this work establishes an important precedent: biometric authentication can be successfully embedded into Indonesian public institutional workflows, and the infrastructure model it employs — combining hardware sensors with a web-based verification backend — is directly transferable to a subsidy distribution context where facial recognition replaces fingerprint capture.

The technical robustness of deep learning-based facial recognition in challenging real-world conditions has been further advanced by Hangaragi et al. [11] (2023), who proposed a Face Mesh and Deep Neural Network model achieving 94.23% accuracy on the LFW benchmark and real-time image streams. By extracting 468 facial landmarks through MediaPipe and complementing this with 3D facial reconstruction (RMSE 2.01), the model substantially outperforms earlier approaches such as Viola-Jones and 3DMM, which achieved accuracies of only 63–77% under non-frontal or variable lighting conditions. The relevance of this work to the present study is twofold: it demonstrates that DNN-based systems can handle the pose and lighting variability characteristic of field environments, and it highlights computational optimization for edge devices as the key remaining challenge for practical deployment.

The challenge of learning reliable facial representations from noisy, real-world data —

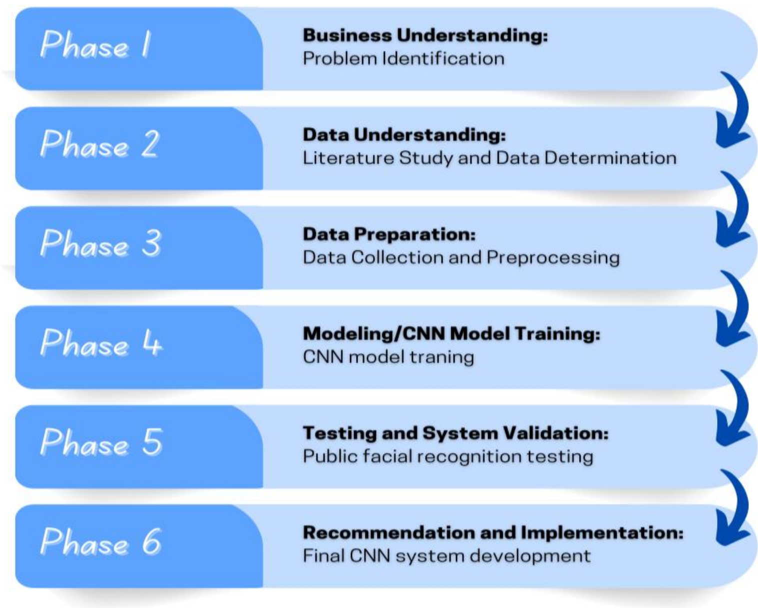
rather than curated benchmark datasets — has been directly addressed by Fredj et al. [12] (2021), who developed a CNN-based face verification framework specifically designed for unconstrained environments. Through aggressive data augmentation and an adaptive fusion of softmax loss and center loss as supervision signals, the system successfully learns discriminative facial embeddings from large-scale data containing significant noise and occlusion. Tested on the Labeled Faces in the Wild and YouTube Faces benchmarks, the approach achieves performance equivalent to state-of-the-art methods, demonstrating that transfer learning combined with robust augmentation strategies can compensate effectively for domain-specific data scarcity — a finding with direct methodological implications for the present study.

Despite this body of evidence, a critical gap persists. CNN-based facial recognition has been extensively validated in commercial and controlled settings — security systems, banking authentication, and academic benchmarks — but its application to public service delivery, and specifically to social subsidy distribution in developing country contexts, remains virtually absent from the literature [13], [14]. The integration of such systems into government programs introduces practical constraints that standard benchmarks do not address: heterogeneous lighting at distribution stalls, limited device quality, demographic attributes such as head coverings, and the absence of large-scale locally curated datasets [15]. These are not peripheral concerns — they are the defining conditions of real-world deployment.

This study addresses that gap by developing and evaluating a CNN-based facial recognition system specifically designed for identifying registered 3-kg LPG subsidy recipients, using a locally acquired biometric dataset from Tangerang City. Three research questions guide the investigation: first, to what extent can a CNN-based facial recognition system accurately identify registered subsidy recipients from a locally collected dataset [16]. Second, can the system operate effectively in real-time at distribution points such as LPG agent stalls [17] and third, what technical and operational challenges must be resolved to support practical field implementation [18].

MATERIALS AND METHODS

This research uses an experimental approach of facial recognition of the subsidized gas recipient using deep learning algorithm [19]. The stage of this research had phases including Business Understanding, Data Understanding, Data Preparation, Modeling/Convolutional Neural Network (CNN) Model Training, Testing and System Validation, the last one is Recommendation and Implementation.



Source: (Research Result, 2025)
Figure 1. Research Design

Based on the research flow diagram in Figure 1, there are 6 phases with the Cross-Industry Process for Data Mining (CRISP-DM) methodology approach [20].

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Phase 1 (Business Understanding) : Activities in this phase include analyzing the 3 kg LPG subsidy policy and existing distribution issues, as well as identifying technology requirements for recipient verification. The expected outcome of this phase is the technical specifications of the required system.

Phase 2 (Data Understanding): This phase focuses on data preparation for CNN model training [21]. The first step is a literature review of facial recognition methods. Second, exploration of simulated datasets. Third, identification of relevant data criteria (image quality, identity labels) [13]. The challenge in this phase is the availability of real-world data on subsidy recipients (requiring collaboration with relevant agencies).

Phase 3 (Data Preparation): The first process in this phase is data collection: initial dataset simulation, then field data (if available). Second, preprocessing: face cropping and pixel size normalization [22]. Third, data augmentation (rotation, flip) to increase dataset variation. Fourth, Labeling: Each facial image is labeled with a subsidy recipient ID. Fifth, Data Distribution: 70% training, 20% validation, 10% test [23].

Phase 4 (CNN Modeling/Training): Select a popular CNN architecture such as MobileNet (lightweight for mobile devices) or ResNet (high accuracy) [24]. Then, train with preprocessed facial input data. Next, optimize parameters using a loss function.

Phase 5 (Model Testing and System Validation) [25]. Conduct field simulations by testing the system at LPG distribution locations, such as gas agents. Afterward, measure system performance, including facial verification speed (seconds per transaction) and error rates (false acceptance/rejection). Furthermore, users in this simulation will be asked to provide feedback and conduct a satisfaction survey regarding ease of use for agents/subsidy recipients.

Phase 6 (CNN System Recommendations and Implementation)[26]: Final development can be carried out by integrating the CNN model into the application interface (e.g., an LPG agent mobile application) and creating a system usage and maintenance guide.

The data collection conducted in this study included a facial dataset of legitimate subsidy recipients, meeting the criteria of being registered in the DTKS, receiving social assistance, and having a registered Population Identification Number (NIK) [27]. A total of 230 facial data were collected from 111 subsidized recipients of Pajang Village, Benda District, Tangerang City. The data collection involved taking frontal facial photographs to create a facial recognition dataset. The collected facial data consisted of frontal facial images with variations in facial expressions, age, lighting conditions, and image resolutions [28], [29].

Source: (Research Result, 2025)

Figure 2. Example of facial data obtained

RESULTS AND DISCUSSION

This study used a local dataset of 3 kg LPG subsidy recipients, consisting of 230 facial images from 111 individuals, with limited variations in pose and lighting. Although this dataset reflects the actual conditions in the field, its relatively small size and limited diversity may affect the robustness of the recognition system. To address this limitation, the study utilized pre-trained models from the InsightFace framework, namely ResNet-IR and MobileFaceNet. These models had previously been trained on large-scale public datasets such as VGGFace2, CASIA-WebFace, and MS-Celeb-1M, but in this research they were directly applied and evaluated only on the local dataset of LPG subsidy recipients.

The experimental results demonstrated that the ResNet-IR model outperformed MobileFaceNet in both facial identification and verification tasks on the local dataset. This result is consistent with findings from previous studies, which indicate that deeper ResNet architectures are capable of extracting more complex and discriminative facial features compared to lightweight models such as MobileFaceNet. However, MobileFaceNet retains the advantage of computational efficiency, making it suitable for scenarios where recognition must be carried out on mobile or resource-constrained devices.

The difference in performance can be explained by the network architectures. ResNet-IR leverages residual connections that facilitate stable gradient flow and enable the learning of more complex facial representations, which leads to higher recognition accuracy. In contrast, MobileFaceNet is optimized for efficiency, focusing on reducing computational cost and memory usage while still maintaining acceptable recognition performance. These results are consistent with previous literature, which suggests that the ResNet architecture, with its deeper layers, is capable of extracting facial features better than lightweight architectures like MobileFaceNet. However, MobileFaceNet still has the advantage of computational efficiency, making it more suitable for implementation on resource-constrained devices, such as smartphones used directly in the field. This difference in results can be explained by the size and diversity of the datasets. Large and varied public datasets provide more stable evaluation results, while small local datasets tend to degrade model performance due to underrepresentation of variations in pose, expression, and lighting.

Furthermore, other technical factors, such as the network architecture, also play a role. ResNet-IR uses residual connections, which improve gradient flow within the network and support the learning of more complex facial features. In contrast, MobileFaceNet was designed with a focus on parameter efficiency for real-time applications. This explains why ResNet-IR produces higher accuracy, while MobileFaceNet is lighter in implementation.

From an application perspective, high accuracy is crucial to avoid misidentifying subsidy recipients, which can impact the distribution of aid inaccurately. Therefore, the use of the ResNet-IR model can be recommended for implementation on servers with adequate resources, while MobileFaceNet remains relevant as an alternative for mobile device-based systems. Increasing the size of the local dataset by adding variations in the faces of subsidy recipients or applying data augmentation is expected to significantly improve the robustness of the system.

Training Model

This study used two main models: ResNet-IR and MobileFaceNet. These two models were chosen because they have different characteristics: ResNet-IR focuses on high accuracy with a deep residual network architecture, while MobileFaceNet is designed as a lightweight, efficient model for resource-constrained devices.

Experiments were conducted using a Google Colab device with a 15GB T4 GPU and 12GB of RAM, Both models were obtained from the InsightFace framework as pre-trained models, which had already been trained on large-scale public facial datasets such as VGGFace2, CASIA-WebFace, and MS-Celeb-1M. In this research, no re-training on those public datasets was conducted; instead, the models were directly applied and evaluated on the local dataset of LPG subsidy recipients. This strategy leverages the transfer learning approach, where knowledge from large-scale training is utilized for specific downstream tasks with smaller datasets.

The local dataset used in this study consisted of 230 facial images from LPG subsidy recipients, with limited variations in lighting and pose. To improve data diversity and prevent overfitting, a validation split was applied so that a portion of the local dataset was reserved for evaluation purposes. This ensured that the models were not only memorizing the input images but were also able to generalize to unseen samples.

Experimental results showed that ResNet-IR achieved a training accuracy of 94.7% on the local dataset, while MobileFaceNet achieved 93.7%. This difference is consistent with their architectural design: ResNet-IR demonstrates stronger capability in extracting complex facial features, while MobileFaceNet emphasizes computational efficiency, enabling faster inference with fewer resources.

Table 1. Accuracy result of training model

Model	Pre-Training Dataset	Evaluation Dataset	Training Accuracy (%)
ResNet-IR	VGGFace2, CASIA WebFace, MS-Celeb-1M	Local Dataset	94.7
MobileFaceNet	VGGFace2, CASIA WebFace, MS-Celeb-1M	Local Dataset	93.7

Source: (Research Result, 2025)

Next, testing was conducted using different test data from the training dataset, to evaluate the model's ability to accurately identify and verify faces in the context of 3 kg LPG subsidy recipients.

Testing Model

The testing phase was conducted to evaluate the ability of the models to recognize the faces of 3 kg subsidized LPG recipients using data that had not been used during the training stage. Two main evaluation scenarios were performed:

1. Face Identification (1:N Matching) In this scenario, the model was required to identify an input facial image from a database of stored embeddings. Each test image was compared against all embeddings in the database, and the identity with the highest similarity score was assigned. Evaluation was carried out using accuracy as the primary metric, while qualitative inspection of inter-class errors was also considered.
2. Face Verification (1:1 Matching) In this scenario, the model was asked to verify whether two facial images belonged to the same

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individual. The test involved comparing positive pairs (two images from the same person) and negative pairs (images from different individuals). Evaluation metrics included precision, recall, F1-score, and ROC curve, which provide insight into the balance between true positives and false positives.

The dataset used in this phase consisted solely of the local dataset, comprising 230 facial images from 111 recipients. Public datasets such as VGGFace2, CASIA-WebFace, and MS-Celeb-1M were not directly used in testing; rather, they were part of the pretraining process for the ResNet-IR and MobileFaceNet models provided by the InsightFace framework. For evaluation, the local dataset was divided into two partitions: a gallery set (used as the reference database of recipients) and a probe set (used as test queries).

This evaluation procedure simulates real-world conditions, where the system must recognize or verify incoming facial images against an existing database of registered subsidy recipients. The results of this stage provide a comprehensive comparison of ResNet-IR and MobileFaceNet in both face identification and verification tasks. The subsequent section presents the quantitative evaluation of these results.

Evaluation Model

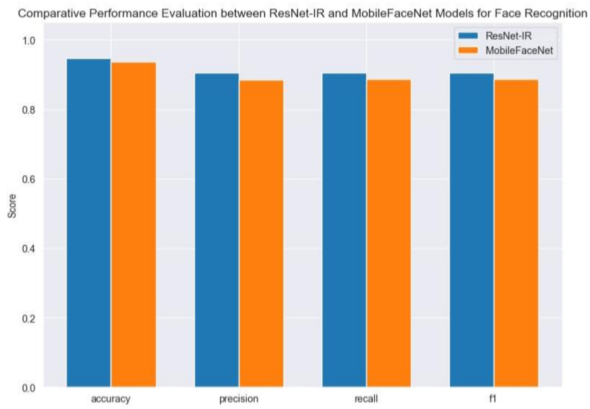
Based on the results of model training on local and public datasets (subsets of VGGFace2, CASIA-WebFace, and MS-Celeb-1M), an evaluation process was conducted to assess model performance in two scenarios: identification (1:N matching) and verification (1:1 matching). The test dataset consisted of 230 facial images from 111 registered recipients, which were divided into gallery images (as the database of known recipients) and probe images (as queries to be identified or verified). Public datasets such as VGGFace2, CASIA-WebFace, and MS-Celeb-1M were not directly used in this evaluation, but served as the pretraining sources for the ResNet-IR and MobileFaceNet models provided by the InsightFace framework.

The evaluation was conducted by calculating accuracy, precision, recall, and F1-score metrics. Additionally, a confusion matrix was used to observe the distribution of errors between classes in the identification scenario, and an ROC curve was used in the verification scenario to evaluate the balance between true positive and false positive rates. The evaluation results are summarized in Tables 2 and Figure 5 which compare the performance of the two tested CNN architectures, ResNet-IR and MobileFaceNet, on various datasets.

Table 2. Performance Comparison of ResNet-IR and MobileFaceNet

Model	Accuracy (%)	Precision	Recall	F1-Score
ResNet-IR	94.7	0.9043	0.9043	0.9043
MobileFaceNet	93.7	0.8859	0.8870	0.8862

Source: (Research Result, 2025)



Source: (Research Result, 2025)
Figure 5. Performance Comparison between ResNet-IR and MobileFaceNet Model

Based on the evaluation results presented in Table 2, the ResNet-IR model consistently achieved higher performance than MobileFaceNet on all datasets used, both public datasets (VGGFace2, CASIA-WebFace, and MS-Celeb-1M) and the local dataset of subsidized LPG recipients. ResNet-IR's accuracy on the local dataset was recorded at 94.7%, with relatively balanced precision, recall, and F1-score values (0.9043, 0.9043, and 0.9043). This indicates that the model is capable of identifying with a low error rate and has good generalization capabilities despite the limited number of local dataset samples.

Meanwhile, the MobileFaceNet model demonstrated quite good performance, with an accuracy at 93.7%. MobileFaceNet's advantage lies in its computational efficiency due to its lighter architecture, making it more suitable for implementation on resource-constrained devices. However, its limited architectural complexity makes its performance slightly lower than ResNet-IR, especially when applied to datasets with diverse poses, lighting, and facial attributes.

Overall, it can be concluded that ResNet-IR is a superior choice for this research, especially in the context of facial recognition of subsidized LPG recipients, which requires a high level of accuracy for identity verification. However, MobileFaceNet remains worthy of consideration if the focus is on field applications with hardware limitations, such as on mobile devices or systems with real-time computing.

Prediction Model

In addition to quantitative evaluation using accuracy, precision, recall, and F1-score metrics, this study also presents model prediction results on several facial samples from a local dataset of LPG subsidy recipients. The purpose of this analysis was to assess the model's ability to perform identification (determining a person's identity from a set of candidates) and verification (ascertaining whether a particular face matches the claimed identity).

In the identification scenario, the ResNet-IR model successfully recognized faces with a very high degree of agreement. For example, an image in the person1 class was correctly predicted as person1 with a similarity score of 0.98. Meanwhile, the MobileFaceNet model also performed well in identification, but there were several cases where the similarity approached the threshold, such as in low-light conditions or non-frontal poses.

In the verification scenario, the model was asked to compare pairs of faces to determine whether they belonged to the same individual. The results show that ResNet-IR achieved a more stable verification rate, with most genuine face pairs successfully verified with a similarity above 0.95, while impostor pairs were rejected with a similarity below 0.5. MobileFaceNet, while still performing well, was more susceptible to borderline cases where the similarity between genuine pairs approached a threshold.

These results demonstrate that the model's predictions are not only accurate in quantitative metrics but also consistent in delivering results that meet the needs of the system in the field. Therefore, the application of CNN models, particularly ResNet-IR, has the potential to be implemented as a mechanism for verifying the identity of 3 kg LPG subsidy recipients with a high level of reliability.

Table 3. Prediction Result of Identification and Verification

Facial Sample (ID)	Model	Prediction	Similarity	Status
	ResNet-IR	orang1 (FITRIA)	0.98	✓Valid
	ResNet-IR	orang2 (NOVIA)	0.96	✓Valid
	MobileFace Net	orang3 (ELIA)	0.91	✓Valid
	MobileFace Net	orang7 (NUR)	0.42	✕Invalid
	ResNet-IR	orang5 (YANAH)	0.95	✓Valid

Source: (Research Result, 2025)

CONCLUSION

This study demonstrates that CNN-based facial recognition, implemented through the InsightFace framework, constitutes a technically viable mechanism for verifying the identity of subsidized LPG recipients under real-world field conditions [30]. The comparative evaluation of ResNet-IR and MobileFaceNet on a locally acquired dataset yields three substantive findings that carry distinct scientific, practical, and methodological implications. From a scientific standpoint, the results confirm that architectural depth translates into measurable recognition superiority even when models are not fine-tuned on domain-specific data. ResNet-IR achieved an accuracy of 94.7% with precision, recall, and F1-score uniformly at 0.9043, outperforming MobileFaceNet across all evaluation metrics (accuracy: 93.7%, F1-score: 0.8862). This performance gap, while numerically modest, is practically significant in the context of identity verification: even marginal improvements in recall directly reduce the rate of false rejections that would deny eligible recipients access to their entitlements.

From a practical standpoint, the findings suggest a deployment bifurcation that aligns with real-world infrastructure constraints. ResNet-IR is recommended for server-side deployment at distribution hubs or central verification nodes where computational resources are adequate. MobileFaceNet, despite its lower accuracy, remains a credible option for mobile or edge-based implementations — an important consideration for agents operating in areas with limited connectivity or using low-specification devices. The primary

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methodological limitation of this study is the relatively small local dataset, comprising 230 images from 111 individuals with constrained variation in pose, lighting, and demographic attributes such as head coverings. This constraint limits the model's generalizability and likely inflates performance metrics relative to fully unconstrained field conditions. Future research should prioritize three directions: first, expanding the dataset to include greater diversity in facial attributes, capture conditions, and geographic coverage; second, conducting fine-tuning experiments on the local dataset to assess whether domain adaptation yields meaningful accuracy gains; and third, integrating the verified model into a real-time mobile application and conducting field trials at actual LPG distribution points to measure system latency, user acceptance, and error rates under operational conditions. Taken together, this study provides the first empirical evidence that deep learning-based biometric verification is deployable within Indonesia's subsidized gas distribution system — establishing a foundation for broader adoption of automated identity verification in public service delivery across the developing world.

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