Insight: Vol. 3, No. 5 October 2025
E-ISSN: 3032-453X P-ISSN: XXXX

Performance Improvement of MobileNetV2 Through Edge-Preserving Bilateral Filter Approach in Face Recognition

Maulana Sujarwadi
STMIK IKMI Cirebon, Indonesia
Email: maulanasujarwadi876@gmail.com

Abstract

The feature extraction process. This study proposes an image preprocessing approach using a Bilateral Filter to enhance the performance of MobileNetV2. The dataset consists of facial images from 82 respondents (comprising a total of approximately 3,444 images, with approximately 42 images captured per respondent across various poses and expressions) collected via Teachable Machine, with dimensions standardized to 224x224 pixels. A quantitative experimental method was conducted, beginning with preprocessing steps such as cropping and resizing. The dataset was partitioned into a 70:20:10 ratio for training, validation, and testing. Furthermore, data augmentation was applied, including position shifts, rotation, zoom, and shear. The model was trained for 50 epochs using the Adam optimizer. The testing results indicate that the integration of the Bilateral Filter significantly improves classification accuracy, increasing it from 69.92% without a filter to 94.31% with the filter. The model demonstrated high precision for most subjects, although variations in accuracy occurred in certain classes due to data diversity. An accuracy improvement of 24.39% confirms that the Bilateral Filter is effective in reducing noise while maintaining the facial edges crucial for Convolutional Neural Network (CNN) feature extraction. This integration provides an optimal solution for face recognition that is both accurate and efficient for implementation on resource-constrained devices.

Keywords: face recognition; mobilenetv2; bilateral filter; deep learning; image preprocessing.

INTRODUCTION

Face recognition technology has become a crucial component in modern security and authentication systems, offering reliable contactless biometrics. Advancements in deep learning, particularly Convolutional Neural Networks (CNN), enable systems to automatically and accurately extract complex visual features. In applications on mobile devices or intelligent systems at the edge of the network (edge devices), lightweight architectures such as MobileNetV2 are highly sought after for their ability to balance computational efficiency and performance (Alonso-fernandez et al., 2024; Chun Hoo et al., 2022). Nevertheless, the implementation of face recognition in real-world environments is often confronted with fluctuating image quality.

The reliability of CNN is heavily dependent on the quality of input data, where the presence of noise or visual degradation can distort the feature extraction process (Tribuana et al., 2026). Research demonstrates that lightweight architectures exhibit higher vulnerability to noise-degraded images compared to deeper models, leading to a significant decline in precision and accuracy levels (Kholwal & Maurya, 2021; Objois et al., 2022). To mitigate the impact of such noise, the image preprocessing stage serves as a fundamental step before data is fed into the CNN model (Soekarta & Ruhana Ku-Mahamud, 2025).

Various conventional spatial filters, such as Mean, Median, and Gaussian filters, are frequently employed to smooth digital images (Sun, 2023). However, literature reviews indicate that these methods possess inherent weaknesses. Both Gaussian and Median filter approaches tend to produce blurring effects that inadvertently eliminate or damage essential edge details in the original image (Novantara & Mutiara, 2021). In the context of face classification, the loss of sharpness in the boundaries of the eyes, nose, or facial contours due to these standard filters can mislead the convolutional layers of the CNN in recognizing unique individual patterns. Therefore, a preprocessing technique is required that is capable of selectively suppressing noise without sacrificing the quality of spatial features (Tribuana et al., 2026).

Addressing this state-of-the-art gap, this study proposes the application of an edge-preserving approach using a Bilateral Filter. Unlike standard linear filters, the Bilateral Filter accounts for both spatial distance and pixel intensity differences, making it highly effective at smoothing noise while firmly maintaining the structural edge boundaries of objects (Anam et al., 2022). For instance, Chu et al. (2024) developed a method combining median and bilateral filters to enhance face recognition under noisy conditions. Although the potential of the Bilateral Filter has been explored in the field of medical imaging, comprehensive studies regarding its integration with lightweight architectures like MobileNetV2 for specific face classification tasks remain very limited.

Consequently, the novelty of this research lies in providing empirical evidence on the extent to which edge-preserving image restoration techniques can maximize lightweight CNN computation. The objective of this study is to evaluate in depth the performance improvement of MobileNetV2 integrated with a Bilateral Filter, examining not only the classification accuracy level but also the stability of metrics in minimizing prediction errors within the model.

METHODS

This study employs a quantitative experimental approach (Ghanad, 2023). Figure 1, illustrates the systematic research stages, beginning with facial dataset collection, followed by preprocessing, application of filtering techniques, data training, model development (classification), model evaluation, and model preservation.

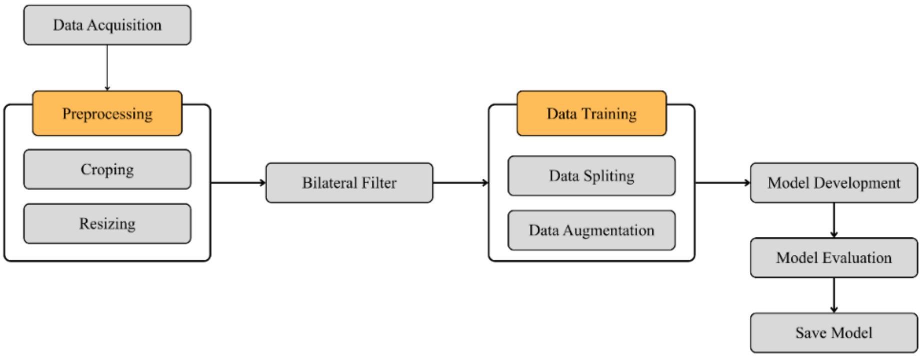


Figure 1. Stages of Research Method

The data collection process in this study was conducted through direct facial image acquisition of 82 respondents. Figure 2, illustrates the sample collection activities performed using the Teachable Machine platform, a web-based instrument developed by Google to facilitate efficient image data collection and processing (Carney et al., 2020). Facial samples were taken from each respondent in various perspectives and expressions to ensure a diversity of features for the model to learn.

All facial images obtained through this instrument were automatically standardized to dimensions of 224x224 pixels. The determination of the 224x224 pixel image size was carried out to align with the input layer specifications of the MobileNetV2 architecture. This dimensional standardization is crucial when utilizing lightweight CNNs to maintain a balance between the depth of extracted spatial features and computational load efficiency during the training process (Chun Hoo et al., 2022).

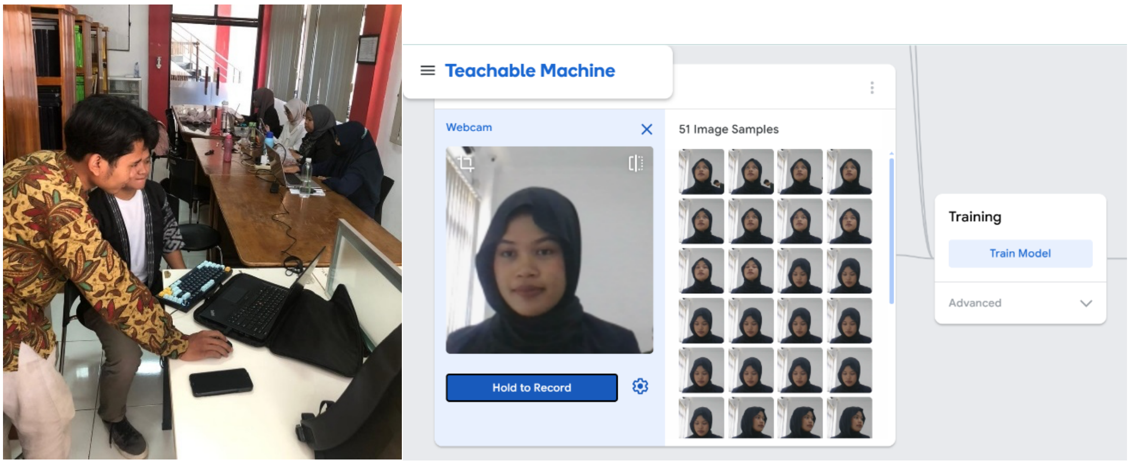


Figure 2. Data Collection via Teachable Machine

The visualization of the dataset samples collected prior to the preprocessing stage is presented in Figure 3. These samples represent the data diversity from 82 respondents with distinct facial characteristics, demonstrating that the raw dataset contains variations in expression, facial perspectives, and diverse lighting conditions. However, these raw acquired images still contain visual noise and pixel intensity fluctuations that may hinder the feature extraction process within the convolutional layers. Consequently, these image samples serve as the primary input to be further processed using image preprocessing techniques to enhance informational quality before the model training phase commences.

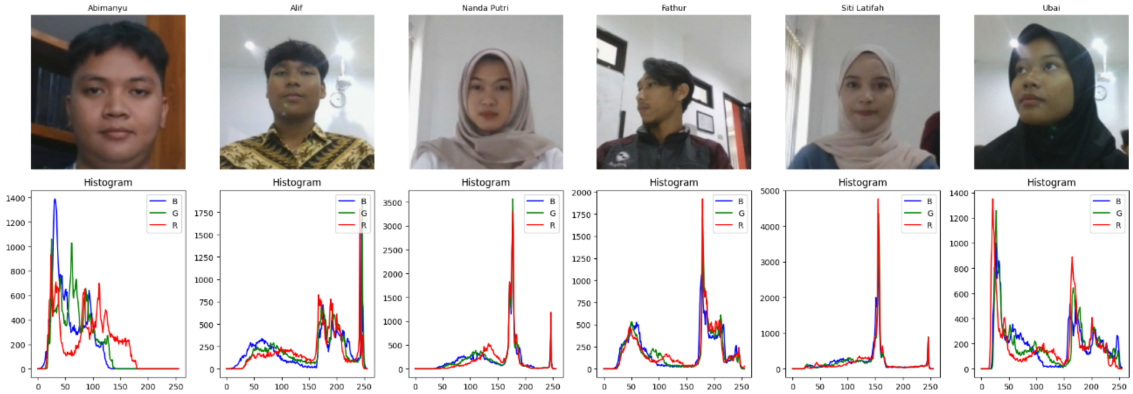


Figure 3. Sample Data generated from Teachable Machine

Subsequently, the preprocessing stage is conducted through cropping, which focuses on eliminating irrelevant background information. The cropped facial images are then resized to dimensions of 224x224 pixels. This isolation of facial features is critical for reducing the computational load while ensuring that the model learns only the essential spatial representations (Xiao et al., 2022). Figure 4, displays the facial images that have undergone the complete preprocessing techniques, along with their respective histograms.

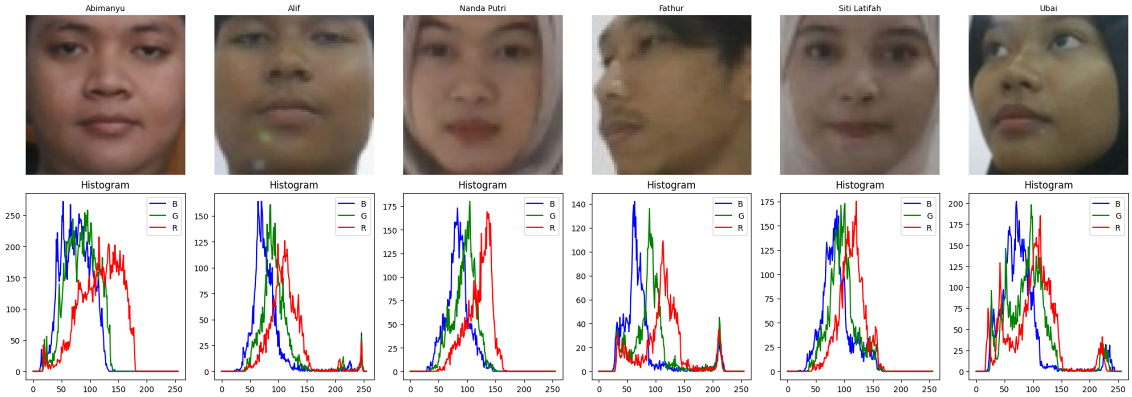


Figure 4. Original Sample Data after Croping

Based on the visual observation in Figure 5, it is evident that the Bilateral Filter is capable of reducing noise and smoothing the facial surface texture without inducing damaging blurring effects. The edge-preserving nature of this filter successfully maintains the sharpness of boundary lines for crucial features, such as the eyes, nose, and jaw contour (Anam et al., 2022).

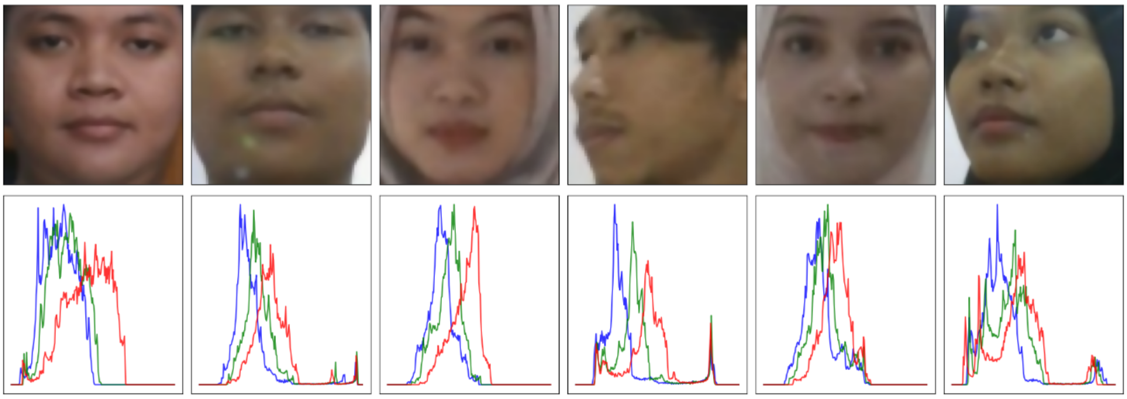


Figure 5. Sample Data after using Bilateral Filter Technique

The data training phase is conducted by partitioning the dataset into three categories: 70% for Training data, 20% for Validation data, and 10% for Testing data. Figure 6, illustrates this proportional data distribution.

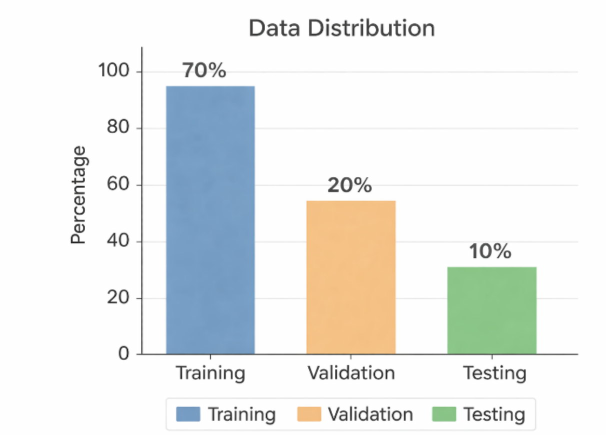


Figure 6. Data Spliting (Propotional Data Training, Validation and Testing)

Data augmentation techniques are employed to expand data diversity by generating new variations from existing facial images, such as through rotation, flipping, or lighting modifications. The use of transformations including rotation, position shifting, zoom, and shear has been proven to enhance the generalization performance of CNN models across various image classification datasets, as detailed in Table 1.

Table 1. Data Augmentation Parameter

Parameter	Description
Rotation_range=20	Randomly rotate the image up to 20 degrees.
Zoom_range=0.1	Randomly zoom in/out the image up to 10% of its original size.
width_shift_range=0.1	Randomly swipes horizontal images up to 0.1 of their widht.
height_shift_range=0.1	Randomly shift vertical images up to 0.1 of their widht.
shear_range=0.1	Apply shear transformation with an intensity of 0.1.
horizontal_flip=True	Flip images horizontally.
fill_mode='nearest'	Fill in empty pixels after tranformation with the nearest pixel value.

Source: Data Processed

The visualization in Figure 7, demonstrates the evident variations across six facial image samples. Each image undergoes transformations such as rotation, zoom, shear, and horizontal flip, resulting in more dynamic facial positions. These augmentation effects are reflected in the histograms, where the distribution of red (R), green (G), and blue (B) color values shows distinct intensity differences for each sample.

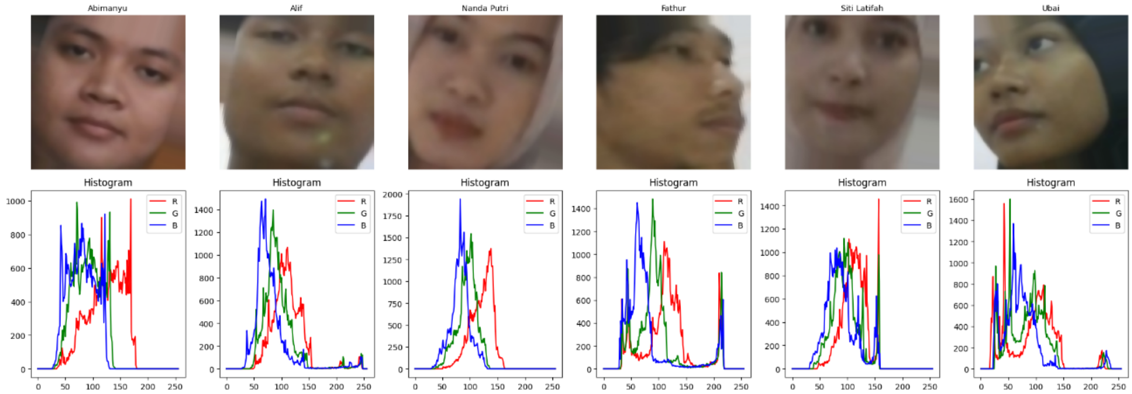


Figure 7. Sample Data after using Augmentation Technique

The model development phase is conducted using the MobileNetV2 architecture, as illustrated in Figure 8. MobileNetV2 is renowned for its lightweight and efficient computation (Adamu et al., 2024). The initial processing stage in the MobileNetV2 architecture begins with the first convolutional layer, which functions as a basic feature extractor. The input image, with a resolution of 224x224 pixels and three color channels (RGB), is processed using a standard 3x3 convolutional filter with a stride of 2. This process produces a feature map of 112x112 dimensions with 32 channels. Each convolution operation is strictly followed by Batch Normalization (BN) and the ReLU6 activation function to maintain numerical stability and introduce efficient non-linearity for mobile devices.

Following the initial feature extraction, the data enters a series of Inverted Residual and Linear Bottleneck blocks, which constitute the core of MobileNetV2's efficiency. Unlike standard residual blocks, these blocks expand the number of channels via a 1x1 convolution (with an expansion factor *t*), apply a 3x3 Depthwise Convolution for computationally efficient feature filtering, and conclude with a 1x1 projection convolution.

This feature extraction process is performed iteratively through several bottleneck block stages with progressively increasing configurations. As the network depth increases, the spatial resolution is gradually reduced (from 112x112 down to 7x7) through stride settings, while the number of channels is increased from 16 to 320 in the final block. This repetitive structure, denoted by x2, x3, and x4, allows the model to capture feature representations ranging from the simplest to more complex semantic features at deeper levels.

In the final section of the architecture, the model transitions from spatial feature maps to class classification through pointwise convolutional and pooling layers. A 1x1 convolutional layer is employed to significantly increase the number of channels to 1,280, providing a rich feature representation prior to the aggregation stage. This data is then processed by Global Average Pooling (GAP), which reduces the 7x7 spatial dimensions into a single average value per channel (1x1). The entire sequence concludes with a final convolutional layer that serves as the classifier, where the Softmax activation function is utilized to generate a probability distribution across the 1.000 target classes.

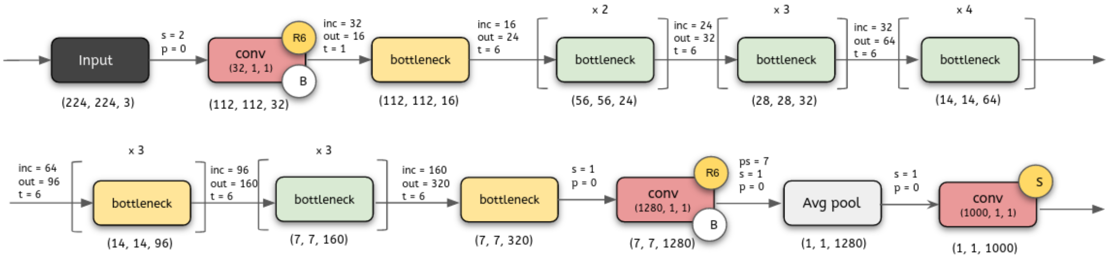


Figure 8. MobileNetV2 Architecture Model

To support the model training and development process on the MobileNetV2 architecture in this study, several key parameters are established, such as the optimizer, learning rate, number of epochs, batch size, loss function, and accuracy metrics (Ahmad, 2023). Detailed information regarding these key parameters can be found in Table 2.

Table 2. Model Parameter

Parameter	Description
Optimasi	Adam
Learning Rate	0.001
Epoch	50
Batch Size	32
Loss Function	Categorical Crossentropy
Metrics	Accuracy

Source: Data Processed

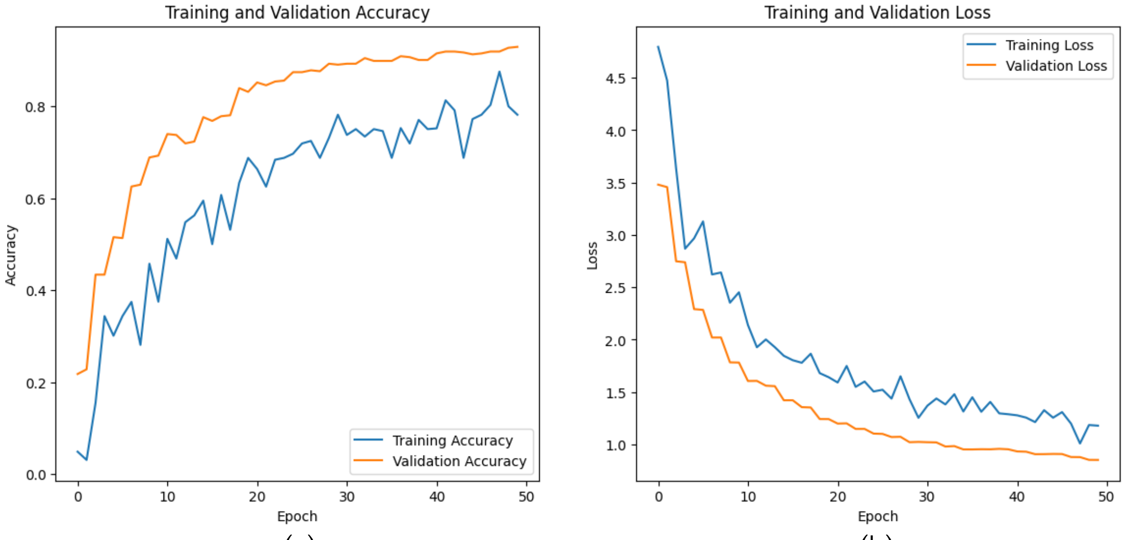
The final stage of this study involves evaluating and preserving the model. The evaluation process is conducted by measuring the model's performance using four standard classification metrics: accuracy, precision, recall, and F1-score. Precision is defined as the ratio of true positive predictions to the total predicted positives (TP / (TP + FP)), measuring the model's exactness in identity attribution. Recall (sensitivity) is calculated as the ratio of true positives to all actual positives (TP / (TP + FN)), reflecting the model's completeness in retrieving correct identities. The F1-score represents the harmonic mean of precision and recall (2 x Precision x Recall / (Precision + Recall)), providing a balanced metric. These metrics were computed per class and aggregated through weighted averaging (Karo-karo et al., 2026).

Upon completion of the evaluation process, the model is saved along with the label encoder, which contains the numerical mapping of facial images, in pickle format.

RESULTS AND DISCUSSION

Based on the Figure 9, the performance of the MobileNetV2 model integrated with a bilateral filter is demonstrated. Subfigure (a) displays the training and validation accuracy process, while subfigure (b) shows the training and validation loss during the models learning phase.

Based on the figure, the MobileNetV2 model with a bilateral filter exhibits a relatively stable learning pattern with high generalization capability. At the onset of training, the model's accuracy is relatively low and increases gradually, reaching an accuracy of 90% to 94% within the 30-50 epoch range. The accuracy graph indicates that training accuracy progressively rises from >0.1 to a peak of >0.8 during the 45-50 epoch interval. Meanwhile, the validation accuracy increases more rapidly and stably from >0.2 to its highest point at >0.8. The slight discrepancy between the training and validation curves suggests that overfitting in the model is relatively low (Rayeni & Naderi, 2025).



(a) (b)

Figure 9. Model Performance

Based on the testing results presented in Table 3, the model's performance in classifying 82 subjects shows significant variation across all evaluation metrics. In general, the model demonstrates a very high precision level, where most classes, such as Abimanyu, Afan, and Dimas, achieve a score of 1.00. This indicates that when the model predicts an identity, the false positive rate is extremely low. However, for several subjects such as Gefira (0.21) and Dede Kuswara (0.27), the low precision values indicate feature ambiguity, causing the model to frequently misidentify other subjects as these individuals.

Viewed from the Recall values, there is a positive correlation between successful feature extraction and the models ability to retrieve information (sensitivity). Subjects achieving a recall value of 1.00 indicate that all test samples (3 samples per class) were correctly identified. Conversely, several classes exhibit recall and precision values of 0.00, such as Haris Burhanudin, Ivan, Khaerul, Linsky, Rijal, Syamsul Hadi, and Topan Rivaldi. The total failure in these classes represents significant challenges in model generalization. From a theoretical perspective, this outcome can be attributed to three compounding factors: (1) insufficient intra-class variation in the training data, which prevents the model from learning robust and discriminative feature representations for these subjects; (2) high inter-class visual similarity, wherein facial features of these subjects may share strong resemblance with other classes, leading the model to assign prediction probability to competing identities; and (3) residual noise in input images that may not have been fully suppressed by the bilateral filter, thereby interfering with the precise localization of discriminative facial landmarks during convolutional feature extraction.

This finding is consistent with the broader deep learning literature, which underscores that lightweight architectures such as MobileNetV2, despite their computational efficiency, remain susceptible to classification collapse when confronted with underrepresented or visually ambiguous classes (Kholwal & Maurya, 2021). Addressing these failure cases in future iterations would require targeted strategies such as class-specific data augmentation, re-sampling to balance class representation, or the application of metric learning approaches to increase the inter-class feature margin.

Overall, the models effectiveness can be concluded through the F1-Score, which represents the harmonic mean of precision and recall. The majority of subjects successfully reached a score range of 0.75 to 1.00, signifying that the implemented MobileNetV2 architecture is robust enough to recognize identity patterns for most subjects. Nonetheless, the constant support value of 3 samples per class indicates that this testing was conducted on a balanced dataset; thus, the performance degradation in certain classes serves as a reference for performing data augmentation or hyperparameter tuning in future model development stages.

Table 3. Model Evaluation

No.	Name	Precision	Recall	F1-Score	Support
1	Abi Arif	1.00	0.33	0.50	3
2	Abimanyu	1.00	1.00	1.00	3
3	Adit	1.00	0.33	0.50	3
4	Afan	1.00	1.00	1.00	3
5	Alif	1.00	0.67	0.80	3
6	Aliya	0.50	0.33	0.40	3
7	Arya	0.60	1.00	0.75	3
8	Arya 2025	1.00	1.00	1.00	3
9	Bagus Mustofa	1.00	0.67	0.80	3
10	Danish	1.00	0.67	0.80	3
11	Daryell	1.00	0.67	0.80	3

No.	Name	Precision	Recall	F1-Score	Support
12	Dede Kuswara	0.27	1.00	0.43	3
13	Dhini	0.67	0.67	0.67	3
14	Dimas	1.00	1.00	1.00	3
15	Dimas Eka	1.00	0.67	0.80	3
16	Egi Alivia	1.00	0.67	0.80	3
17	Fairuzzahran Bachtiar	0.50	0.67	0.57	3
18	Fajar	1.00	0.33	0.50	3
19	Fajar Febryano	1.00	1.00	1.00	3
20	Fajar Ma'ruf	1.00	1.00	1.00	3
21	Fakhri	1.00	1.00	1.00	3
22	Fathur	0.50	1.00	0.67	3
23	Firosy	0.50	1.00	0.67	3
24	Galang	0.50	0.67	0.57	3
25	Gatha	1.00	1.00	1.00	3
26	Gefira	0.21	1.00	0.35	3
27	Haris Burhanudin	0.00	0.00	0.00	3
28	Haydar Rahman	1.00	1.00	1.00	3
29	Hendra	0.67	0.67	0.67	3
30	Ilham Tri Cahya	0.60	1.00	0.75	3
31	Iman	0.33	0.33	0.33	3
32	Indrawan	0.60	1.00	0.75	3
33	Ivan	0.00	0.00	0.00	3
34	Khaerul	0.00	0.00	0.00	3
35	Leo Ardiyansyah Jailani	0.67	0.67	0.67	3
36	Linsky	0.00	0.00	0.00	3
37	Maulana Sujarwadi	1.00	0.67	0.80	3
38	Muhammad Avin Maulana	0.75	1.00	0.86	3
39	Muhammad Ibnu	1.00	1.00	1.00	3
40	Nanda Putri	0.60	1.00	0.75	3
41	Nasywa	1.00	1.00	1.00	3
42	Niara Aprilia	1.00	1.00	1.00	3
43	Nihlah	1.00	0.33	0.50	3
44	Nizar Firmansyah	0.75	1.00	0.86	3
45	Novi Fitriani	0.38	1.00	0.55	3
46	Nurasifa	0.50	0.67	0.57	3
47	Poetra Ebeline	1.00	0.67	0.80	3
48	Pria Budi	1.00	1.00	1.00	3
49	Putri Nabila	1.00	0.33	0.50	3
50	Qonita	1.00	1.00	1.00	3
51	Rafi Dwi Candra Murti	1.00	1.00	1.00	3

No.	Name	Precision	Recall	F1-Score	Support
52	Rafi Erlangga	1.00	0.67	0.80	3
53	Rauzzan	1.00	1.00	1.00	3
54	Reyhan	1.00	0.67	0.80	3
55	Rian Afriyansyah	0.38	1.00	0.55	3
56	Rijal	0.00	0.00	0.00	3
57	Rika	1.00	0.67	0.80	3
58	Riyan Setiawan	0.50	0.33	0.40	3
59	Robi Muhammad	1.00	1.00	1.00	3
60	Sabrina Khoirunnisa	0.33	0.33	0.33	3
61	Salman Al farizi	0.50	0.67	0.57	3
62	Salsa Nabila	1.00	0.33	0.50	3
63	Satria	0.75	1.00	0.86	3
64	Septia Dewi	1.00	1.00	1.00	3
65	Sindi Amelia	0.75	1.00	0.86	3
66	Siti Latifah	1.00	0.33	0.50	3
67	Siti Nikmat	1.00	0.67	0.80	3
68	Siti Nur Fadillah	0.33	0.33	0.33	3
69	Sitimasripatul Hawa	0.60	1.00	0.75	3
70	Soleh	0.50	0.33	0.40	3
71	Sulistina Juliyanti	1.00	0.67	0.80	3
72	Syamsul Hadi	0.00	0.00	0.00	3
73	Talita	1.00	1.00	1.00	3
74	Topan Rivaldi	0.00	0.00	0.00	3
75	Ubai	1.00	1.00	1.00	3
76	Viran	1.00	0.33	0.50	3
77	Wandi	1.00	1.00	1.00	3
78	Wichal Aditiya Purnama	0.50	0.67	0.57	3
79	Winarti	0.67	0.67	0.67	3
80	Yogafratama	1.00	0.33	0.50	3
81	Yurdika	1.00	1.00	1.00	3
82	Yuslia Devitri	1.00	0.67	0.80	3

Source: Data Processed

Based on the data presented in the Table 4, a significant positive correlation exists between the application of image preprocessing techniques and the model's accuracy level. Testing without the use of a filter yielded an accuracy of only 69.92%. This indicates that the presence of noise in the original images substantially interferes with the model's feature extraction process, leading to suboptimal classification performance.

A drastic performance improvement occurred when the bilateral filter technique was implemented, with accuracy increasing to 94.31%. This 24.39%

increase proves that the bilateral filter is highly effective in reducing noise without eliminating crucial edge-preserving information necessary for object identification. Theoretically, the ability of this filter to maintain the sharpness of boundaries between image regions enables the MobileNetV2 model to capture texture patterns and shapes with far greater precision compared to images that have not undergone the filtering process.

Table 4. Model Accuracy of Bilateral Filter and No Filter Technique

No.	Technique	Accuracy
1	Bilateral Filter	94.31%
2	No Filter	69.92%

Source: Data Processed

This study aligns with previous research, where bilateral filters have proven highly effective in overcoming noise while preserving image edges and maintaining accuracy in filtered models (Anam et al., 2022). This finding is supported by the high accuracy achieved by the MobileNetV2 model through the application of the bilateral filter. Furthermore, a study by Chu et al. (2024) demonstrated that the integration of median and bilateral filters can enhance accuracy in face recognition images under noisy conditions. This is corroborated by the results of this study, which show a significant increase in accuracy between the model without a filter and the one utilizing the bilateral filter.

CONCLUSION

Based on the findings of this study, it can be concluded that the integration of the Edge-Preserving Bilateral Filter technique during image preprocessing exerts a highly significant impact on enhancing the performance of the MobileNetV2 model in face recognition tasks. Experimental results demonstrate that the application of this filter drastically increases system accuracy from 69.92% to 94.31%. This success is driven by the ability of the Bilateral Filter to reduce noise without blurring crucial image edge details, thereby enabling the MobileNetV2 architecture to extract biometric features with far greater precision and stability compared to the use of unfiltered image data.

Architecture offers an optimal solution for developing face recognition systems that are accurate yet efficient for implementation on computationally constrained devices. Future research is recommended to explore the following directions: (1) integration of adaptive or guided bilateral filters, which dynamically adjust filtering parameters based on local image statistics to further improve edge preservation under heterogeneous noise conditions; (2) investigation of hybrid preprocessing architectures that combine bilateral filtering with contrast-limited adaptive histogram equalization (CLAHE) or wavelet-based denoising to address additional degradation factors such as illumination variation.

REFERENCES

Adamu, M. J., Kawuwa, H. B., Qiang, L., Nyatega, C. O., Younis, A., Fahad, M., & Dauya, S. S. (2024). Efficient And Accurate Brain Tumor Classification Using Hybrid Mobilenetv2 – Support Vector Machine For Magnetic Resonance Imaging Diagnostics In Neoplasms. *Brain Sciences*, *14*(1178), 1–23.

Ahmad, S. (2023). An Efficient Optimization Technique For Training Deep Neural Networks. *Mathematics*, *11*(1360), 1–22.

Alonso-Fernandez, F., Hernandez-Diaz, K., Maria, J., Rubio, B., Tiwari, P., & Bigun, J. (2024). Deep Network Pruning : A Comparative Study On Cnns In Face Recognition. *Elsevier*, 1–8.

Anam, C., Naufal, A., Sutanto, H., Adi, K., & Dougherty, G. (2022). Impact Of Iterative Bilateral Filtering On The Noise Power Spectrum Of Computed Tomography Images. *Algorithms*, *15*(374), 1–15.

Carney, M., Webster, B., & Jongejan, J. (2020). Teachable Machine : Approachable Web-Based Tool For Exploring Machine Learning Classification. *Chi*, 1–8.

Chu, Z., Weng, G., & Guo, L. (2024). *Research On Image Denoising Algorithm Based On Adaptive Bilateral Filter And Median Filter Fusion*. *4*(October), 69–83. Https://Doi.Org/10.69987/Jacs.2024.41006

Chun Hoo, S., Ibrahim, H., & Azmin Suandi, S. (2022). Convfacenext : Lightweight Networks For Face Recognition. *Mathematics*, *10*(3592), 1–28.

Ghanad, A. (2023). An Overview Of Quantitative Research Methods. *International Journal Of Multidisciplinary Research And Analysis*, *06*(08), 3794–3803. Https://Doi.Org/10.47191/Ijmra/V6-I8-52

Karo-Karo, J., Ardan Raihan, S., Sumanto, R., Budiawan, I., Pakpahan, R., & Christian, A. (2026). Heart Disease Prediction Using Machine Learning Algorithms Based On Health Indicators With Random Forest. *Jurnal Ilmiah Sitem Informasi (Jusi)*, *5*(1), 84–95.

Kholwal, R., & Maurya, S. (2021). A Comparative Approach On Classification Of Images With Convolutional Neural Networks. *International Journal Of Engineering And Advanced Technology*, *10*(4), 201–205. Https://Doi.Org/10.35940/Ijeat.D2483.0410421

Novantara, P., & Mutiara, J. (2021). Perbandingan Metode Gaussian Filter Dengan Median Filter Dalam Mereduksi. *Jejaring (Jurnal Teknologi Dan Manajemen Informatika)*, *6*(1), 19–25.

Objois, É., Okumus, K., & Bahler, N. (2022). Target Aware Poisson-Gaussian Noise Parameters Estimation From Noisy Images. *Computational Photography*, 1–11.

Rayeni, A., & Naderi, H. (2025). Predicting The Canadian Yield Curve Using Machine Learning Techniques. *International Journal Of Financial Studies*, *13*(170), 1–30.

Soekarta, R., & Ruhana Ku-Mahamud, K. (2025). Recent Facial Image Preprocessing Techniques: A Review. *Engineering Proceedings*, *84*(39), 1–11. Https://Doi.Org/10.3390/26734591

Sun, M. (2023). Comparison Of Processing Results Of Median Filter And Mean Filter On Gaussian Noise. *Proceedings Of The 3rd International Conference On*

Signal Processing And Machine Learning, 779–785. Https://Doi.Org/10.54254/2755-2721/5/20230702

Tribuana, D., Hazriani, & Arda, A. L. (2026). Jurnal Resti Image Preprocessing Approaches Toward Better Learning Performance With Cnn. *Jurnal Resti (Rekayasa Sistem Dan Teknologi Informasi)*, *8*(1), 1–9.

Xiao, J., Jiang, G., & Liu, H. (2022). Eai Endorsed Transactions A Lightweight Face Recognition Model Based On Mobilefacenet For Limited Computation Environment. *Eai Endorsed Transactions On Internet of Things*, *7*(27), 1–9.
