Development of a CNN-Based Household Waste Image Classification Model for Automatic Identification

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***Abstract**. The problem of household waste in Indonesia remains a major challenge due to the low level of waste sorting and the lack of technology utilization in the waste identification process. This study aims to develop a Deep Learning-based inorganic waste identification system using the Convolutional Neural Network (CNN) method to improve the accuracy of automatic classification in the household environment. The research method used is an experiment with a quantitative approach. The dataset used consists of 92 images of inorganic waste covering the categories of plastic, paper, glass, and metal. The data went through a preprocessing stage in the form of image resizing to 224 × 224 pixels, normalization, and data augmentation, then divided into training and testing data with a ratio of 80:20. The CNN model was trained using variations in epoch parameters, batch size, and learning rate, then evaluated using metrics of accuracy, precision, recall, F1-score, and confusion matrix. The results showed that the training parameters had a significant effect on model performance. The optimal value was obtained at epoch 20 with 97% accuracy, a batch size of 8 with 97% accuracy, and a learning rate of 1×10^{-3} with 90% accuracy. The best parameter combination produced a model with 97% classification accuracy, along with balanced precision, recall, and F1-score values. These results demonstrate the effectiveness of the CNN method in automatically identifying inorganic waste types. The developed system has the potential to be applied in household environments to assist waste sorting, improve waste management efficiency, and support environmental conservation by raising public awareness of the importance of sustainable waste management. Although the model achieved 97% accuracy under a single 80:20 train-test split, its performance decreased substantially to 32.69% ± 6.93% under stratified 5-fold cross-validation, indicating potential overfitting and limited generalization.*

***Keywords** - Deep Learning, Convolutional Neural Network (CNN), waste classification, image processing, automatic waste sorting.*

***Abstrak**. Masalah sampah rumah tangga di Indonesia masih menjadi tantangan besar akibat rendahnya tingkat pemilahan sampah dan kurangnya pemanfaatan teknologi dalam proses identifikasi sampah. Penelitian ini bertujuan untuk mengembangkan sistem identifikasi sampah anorganik berbasis *Deep Learning* menggunakan metode *Convolutional Neural Network* (CNN) guna meningkatkan akurasi klasifikasi otomatis di lingkungan rumah tangga. Metode penelitian yang digunakan adalah eksperimen dengan pendekatan kuantitatif. Dataset yang digunakan terdiri dari 92 citra sampah anorganik yang mencakup kategori plastik, kertas, kaca, dan logam. Data tersebut melalui tahap pra-pemrosesan berupa penyesuaian ukuran citra (*resizing*) menjadi 224 × 224 piksel, normalisasi, dan augmentasi data, kemudian dibagi menjadi data pelatihan dan pengujian dengan rasio 80:20. Model CNN dilatih menggunakan variasi parameter *epoch*, *batch size*, dan *learning rate*, lalu dievaluasi menggunakan metrik akurasi, presisi, *recall*, *F1-score*, dan matriks konfusi (*confusion matrix*). Hasil penelitian menunjukkan bahwa parameter pelatihan memiliki pengaruh signifikan terhadap kinerja model. Nilai optimal diperoleh pada *epoch* 20 dengan akurasi 97%, *batch size* 8 dengan akurasi 97%, dan *learning rate* 1×10^{-3} dengan akurasi 90%. Kombinasi parameter terbaik menghasilkan model dengan akurasi klasifikasi 97%, serta nilai presisi, *recall*, dan *F1-score* yang seimbang. Hasil ini menunjukkan efektivitas metode CNN dalam mengidentifikasi jenis sampah anorganik secara otomatis. Sistem yang dikembangkan ini berpotensi diterapkan di lingkungan rumah tangga untuk membantu pemilahan sampah, meningkatkan efisiensi pengelolaan sampah, dan mendukung pelestarian lingkungan dengan meningkatkan kesadaran masyarakat akan pentingnya pengelolaan sampah yang berkelanjutan. Meskipun model mencapai akurasi 97% pada satu kali pembagian data latih-uji (rasio 80:20), kinerjanya menurun secara signifikan menjadi 32,69% ± 6,93% saat menggunakan metode *stratified 5-fold cross-validation*, yang mengindikasikan adanya potensi *overfitting* dan kemampuan generalisasi yang terbatas.*

***Kata Kunci** - Deep Learning, Convolutional Neural Network (CNN), klasifikasi limbah, pengolahan citra, pemilahan limbah otomatis.*

I. PENDAHULUAN

Pengelolaan sampah tetap menjadi salah satu tantangan lingkungan utama yang dihadapi Indonesia akibat besarnya volume sampah yang dihasilkan dari aktivitas rumah tangga dan kegiatan sehari-hari lainnya[1]. Data pengelolaan sampah nasional yang disediakan melalui Sistem Informasi Pengelolaan Sampah Nasional (SIPSN) menunjukkan bahwa timbulan sampah masih sangat besar, sementara sebagian besar sampah belum dikelola dengan baik[1]. Pemilahan sampah dari sumbernya merupakan komponen penting dalam pengelolaan sampah rumah tangga karena pemisahan sampah berdasarkan jenisnya dapat mempermudah proses daur ulang dan pengolahan selanjutnya[2]. Namun, pemilahan sampah rumah tangga masih menjadi tantangan besar di Indonesia, sehingga diperlukan pendekatan yang dapat mendukung pemilahan sampah yang lebih efisien di tingkat sumber[2]. Oleh karena itu, klasifikasi sampah otomatis muncul sebagai pendekatan potensial untuk mendukung pemilahan sampah yang lebih efisien dan pengelolaan sampah yang berkelanjutan[3][4]. Perkembangan terkini dalam Kecerdasan Buatan (AI), khususnya Deep Learning, telah membuka peluang untuk mengembangkan sistem klasifikasi sampah berbasis citra [3], [4]. Metode berbasis Deep Learning telah banyak diteliti untuk klasifikasi sampah otomatis karena metode ini mampu mempelajari fitur-fitur pembeda secara langsung dari data citra [3], [10], [21]. Salah satu arsitektur yang paling banyak digunakan untuk klasifikasi citra adalah Convolutional Neural Network (CNN), yang mampu mempelajari fitur spasial dan pola visual dari citra secara otomatis [4], [5]. Kemampuan model berbasis CNN dalam mengekstraksi karakteristik visual menjadikannya cocok untuk mengidentifikasi berbagai kategori sampah dari citra digital [5], [6]. Beberapa penelitian sebelumnya telah mengkaji pendekatan berbasis CNN untuk klasifikasi sampah. Bahagia dan Akbar melaporkan bahwa CNN dapat digunakan untuk membedakan kategori sampah organik dan anorganik [6]. Demikian pula, Diqi mengembangkan sistem klasifikasi sampah berbasis CNN dan melaporkan akurasi klasifikasi yang tinggi pada dataset yang dievaluasi [5]. Sadida Aulia dkk. meneliti klasifikasi sampah rumah tangga menggunakan pendekatan berbasis CNN [8]. Selanjutnya, Agustiani dkk. membandingkan beberapa arsitektur deep learning, termasuk EfficientNetB3, MobileNetV2, dan ResNet50, untuk klasifikasi sampah dan melaporkan bahwa EfficientNetB3 mencapai kinerja terbaik di antara arsitektur yang dievaluasi [7]. Penelitian lain juga telah mengkaji pendekatan berbasis CNN untuk klasifikasi sampah multi-kelas [15], [17], [19], [20]. Meskipun berbagai penelitian telah menunjukkan potensi deep learning untuk klasifikasi limbah, masih terdapat perbedaan dalam hal ukuran dataset, kategori limbah, arsitektur model, dan kondisi eksperimental [3], [7], [9], [10]. Beberapa penelitian menggunakan dataset limbah yang tersedia untuk umum atau dataset yang dikumpulkan dalam kondisi pengambilan gambar tertentu. Sebagai contoh, penelitian klasifikasi limbah rumah tangga sebelumnya telah mengkaji dataset yang memuat kategori limbah dan karakteristik citra yang berbeda [8]–[10]. Akibatnya, kinerja model yang diperoleh dari suatu dataset tertentu belum tentu mencerminkan kinerja dalam kondisi citra rumah tangga yang berbeda. Lingkungan rumah tangga yang nyata dapat menghadirkan variasi dalam hal pencahayaan, latar belakang, orientasi objek, posisi objek, dan kualitas citra. Faktor-faktor ini dapat memengaruhi karakteristik visual yang tersedia bagi model klasifikasi citra. Oleh karena itu, penelitian sebelumnya telah mengkaji klasifikasi limbah rumah tangga dan deteksi limbah secara real-time menggunakan pendekatan deep learning [9], [23]. Hal ini menunjukkan bahwa evaluasi metode klasifikasi limbah dalam lingkungan rumah tangga tetap relevan. Selain arsitektur model, konfigurasi pelatihan dapat memengaruhi kinerja model CNN. Parameter seperti jumlah epoch, ukuran batch, dan laju pembelajaran (learning rate) menentukan bagaimana model belajar dari data pelatihan dan dapat memengaruhi kinerja klasifikasi yang dihasilkan. Penelitian klasifikasi limbah sebelumnya sebagian besar berfokus pada pengembangan dan evaluasi model klasifikasi menggunakan berbagai arsitektur CNN atau deep learning [5][10], [14][21]. Namun, lebih sedikit penelitian yang secara khusus menekankan analisis empiris terkontrol mengenai pengaruh hiperparameter pelatihan terhadap kinerja CNN dalam skenario data terbatas. Luntungan mengembangkan sistem klasifikasi limbah otomatis menggunakan deep learning berbasis CNN untuk mendukung pengelolaan limbah cerdas [18]. Simbolon dkk. meneliti klasifikasi citra limbah rumah tangga menggunakan model deep learning dan mempertimbangkan empat kategori limbah anorganik rumah tangga, yaitu kaca, plastik, logam, dan kertas [9]. Penelitian-penelitian tersebut menunjukkan kelayakan penerapan deep learning untuk klasifikasi limbah rumah tangga. Akan tetapi, penelitian ini secara khusus berfokus pada evaluasi empiris terhadap hiperparameter pelatihan CNN tertentu, bukan mengusulkan arsitektur CNN yang baru. Oleh karena itu, penelitian ini tidak mengklaim adanya kebaruan dalam penerapan CNN untuk klasifikasi limbah rumah tangga itu sendiri. Sebaliknya, kontribusinya terletak pada dalam menyajikan evaluasi empiris yang terkontrol mengenai sensitivitas kinerja klasifikasi CNN terhadap hiperparameter pelatihan tertentu—yaitu jumlah epoch, ukuran batch, dan laju pembelajaran—dalam skenario data berskala kecil. Analisis ini dilanjutkan dengan eksperimen konfirmasi untuk menentukan konfigurasi pelatihan yang praktis dan dapat direproduksi bagi dataset citra limbah rumah tangga berskala kecil. Penelitian ini bertujuan mengembangkan sistem identifikasi otomatis limbah rumah tangga berbasis Deep Learning dengan metode Convolutional Neural Network (CNN). Sistem ini dirancang untuk mengklasifikasikan empat kategori limbah anorganik—yakni plastik, kertas, kaca, dan logam—menggunakan data citra yang diperoleh dari dataset yang tersedia untuk umum. Selain itu, studi ini mengevaluasi dampak beberapa parameter pelatihan, termasuk jumlah epoch, ukuran batch, dan laju pembelajaran, terhadap kinerja klasifikasi. Hasil penelitian ini diharapkan dapat memberikan wawasan empiris mengenai pelatihan CNN dalam kondisi data terbatas serta berkontribusi pada pengembangan sistem klasifikasi limbah berbasis citra yang praktis untuk mendukung kegiatan pemilahan limbah rumah tangga.

1.1 Penelitian terdahulu / Literature Review

Study	Method/Architecture	Dataset Size	Classes	Accuracy
Diqi (2022)	**CNN**	**22,564**	**2**	**99.69%**
Bahagia & Akbar (2024)	**CNN**	**25,112**	**2**	**95%**
Agustiani et al. (2025)	**EfficientNetB3**	**4,650**	**6**	**93%**
Simbolon et al. (2025)	**MobileNetV2**	**NR**	**4**	**>80%**
Luntungan (2025)	**CNN**	**NR**	**2**	**94.86%***
This study	**CNN + Hyperparameter Optimization**	**92**	**4**	**97%**

Tabel 1. Ringkasan Perbandingan Studi Terdahulu mengenai Klasifikasi Limbah

Berdasarkan perbandingan yang disajikan pada Tabel 1, studi-studi terdahulu menunjukkan bahwa metode deep learning, khususnya Convolutional Neural Networks (CNN) dan pendekatan transfer learning, mampu mencapai kinerja tinggi dalam klasifikasi limbah. Sebuah studi menggunakan CNN dengan kumpulan data (dataset) sebanyak 22.564 gambar yang mencakup dua kelas limbah dan mencapai akurasi sebesar 99,69% [5]. Demikian pula, studi lain menerapkan CNN pada 22.564 gambar dari dua kategori limbah dan melaporkan akurasi sebesar 95% [6]. Sebuah studi perbandingan terhadap beberapa arsitektur transfer learning menggunakan dataset sebanyak 4.650 gambar yang terbagi dalam enam kelas limbah [7]. Dalam studi tersebut, EfficientNetB3 mencapai akurasi tertinggi sebesar 93%, diikuti oleh ResNet50 dengan akurasi sekitar 91%, sedangkan MobileNetV2 mencapai sekitar 70–73%. Studi lain menggunakan MobileNetV2 untuk klasifikasi limbah rumah tangga dengan empat kelas dan melaporkan akurasi di atas 80% [8]. Selain itu, sistem klasifikasi limbah berbasis CNN mencapai akurasi pelatihan sebesar 94,86% [9]. Dibandingkan dengan studi-studi terdahulu tersebut, penelitian ini menggunakan dataset yang jauh lebih kecil, yaitu hanya terdiri dari 92 gambar yang terbagi ke dalam empat kelas limbah. Konfigurasi CNN terbaik yang diperoleh melalui evaluasi hiperparameter mencapai akurasi 97% dengan menggunakan 20 epoch, ukuran batch 8, dan laju pembelajaran (learning rate) 1×10^{-3}. Namun, hasil ini harus ditafsirkan secara hati-hati karena evaluasi dilakukan menggunakan dataset yang terbatas dan satu kali pembagian data latih-uji (train–test split). Oleh karena itu, akurasi 97% tersebut tidak boleh dianggap sebagai bukti bahwa model yang diusulkan mengungguli studi terdahulu yang menggunakan dataset jauh lebih besar. Sebaliknya, hasil tersebut menunjukkan bahwa konfigurasi hiperparameter yang dipilih mampu menghasilkan kinerja klasifikasi yang baik dalam kondisi eksperimental penelitian ini. Secara keseluruhan, studi-studi terdahulu umumnya menggunakan dataset yang lebih besar dan berfokus pada penerapan atau perbandingan arsitektur CNN dan transfer learning. Sebaliknya, penelitian ini menekankan pada evaluasi empiris hiperparameter CNN—khususnya jumlah epoch, ukuran batch, dan laju pembelajaran—untuk klasifikasi limbah rumah tangga empat kelas menggunakan dataset yang terbatas. Oleh karena itu, kontribusi penelitian ini bukan untuk mengklaim akurasi yang lebih unggul dibandingkan pendekatan-pendekatan sebelumnya, melainkan untuk mengkaji bagaimana konfigurasi hiperparameter memengaruhi kinerja klasifikasi CNN dalam kondisi keterbatasan data.

II. METODE

Penelitian ini menggunakan metode eksperimental dengan pendekatan kuantitatif untuk mengembangkan dan mengevaluasi sistem klasifikasi sampah rumah tangga otomatis berbasis Deep Learning menggunakan metode Convolutional Neural Network (CNN). Pendekatan eksperimental dipilih untuk mengkaji pengaruh beberapa parameter pelatihan terhadap kinerja model klasifikasi serta menentukan konfigurasi parameter optimal guna mencapai akurasi klasifikasi tertinggi. Untuk menentukan konfigurasi pelatihan CNN yang optimal, dilakukan tiga eksperimen hiperparameter: variasi epoch, variasi batch size, dan variasi learning rate. Setiap eksperimen dievaluasi menggunakan metrik akurasi, presisi, recall, dan F1-score. Hanya satu parameter yang diubah pada satu waktu sementara konfigurasi pelatihan lainnya tetap dipertahankan untuk memastikan perbandingan yang adil. Secara umum, metode yang digunakan mencakup hal-hal berikut:

1.1 Alur Penelitian

Penelitian ini dilaksanakan melalui beberapa tahapan, yaitu pengumpulan data, pra-pemrosesan data, pembagian dataset, pelatihan model CNN, evaluasi model, dan implementasi sistem. Alur penelitian secara keseluruhan diilustrasikan pada Gambar 1.

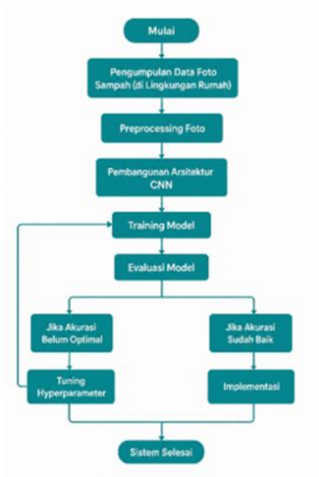

Figure 1. Research Flowchart

Proses ini dimulai dengan mengumpulkan dataset citra limbah dari sumber daring. Citra yang terkumpul kemudian diproses awal untuk meningkatkan kualitas data dan mempersiapkannya bagi proses pelatihan. Setelah tahap pra-pemrosesan, dataset dibagi menjadi data pelatihan dan data pengujian. Model CNN dilatih menggunakan dataset pelatihan dengan berbagai kombinasi nilai epoch, ukuran batch, dan laju pembelajaran (learning rate). Selanjutnya, model yang telah dilatih dievaluasi menggunakan dataset pengujian. Akhirnya, model dengan kinerja terbaik diintegrasikan ke dalam sistem klasifikasi limbah otomatis. Penyesuaian hiperparameter dilakukan secara bertahap menggunakan strategi one-factor-at-a-time (OFAT). Pengaruh jumlah epoch, ukuran batch, dan laju pembelajaran dievaluasi secara independen sementara parameter lainnya dijaga tetap konstan. Nilai terbaik yang diperoleh untuk setiap parameter kemudian digunakan dalam konfigurasi akhir. Selanjutnya, eksperimen konfirmasi dilakukan menggunakan kombinasi nilai hiperparameter terpilih tersebut.

2.2 Pengumpulan Dataset

Dataset ini terdiri dari 92 citra asli yang mewakili empat kategori limbah rumah tangga. Karena augmentasi data dilakukan secara online selama proses pelatihan, citra hasil augmentasi tidak disimpan secara permanen sebagai berkas tambahan. Sebaliknya, transformasi citra dibangkitkan secara dinamis untuk setiap batch pelatihan. Dengan 73 citra pelatihan, ukuran batch sebesar 8, dan 25 epoch pelatihan, proses pelatihan melibatkan 10 langkah per epoch; hal ini setara dengan 80 instans citra yang diproses per epoch dan 2.000 paparan citra efektif selama keseluruhan proses pelatihan. Dengan demikian, dataset fisik tetap berjumlah 92 citra asli, sementara jumlah efektif instans citra pelatihan meningkat melalui augmentasi online.[8][9] Limbah organik dan residu tidak disertakan dalam penelitian ini karena identifikasinya mungkin memerlukan karakteristik non-visual—seperti bau, kadar air, atau komposisi material—yang berada di luar cakupan pendekatan klasifikasi citra yang diusulkan.

Parameter	Value
Original images	92
Number of classes	4

Training images	73
Testing images	19
Image size	224 × 224 pixels
Batch size	8
Epochs	25
Augmentation	Online/dynamic
Effective training image exposures	2,000

Table 2. Dataset and Training Configuration

2.3 Memproses data

Pra-pemrosesan data dilakukan untuk meningkatkan kualitas citra dan ketangguhan model. Tahap pra-pemrosesan ini mencakup langkah-langkah berikut: Pengubahan Ukuran Citra (Image Resizing)—seluruh citra diubah ukurannya menjadi 224 × 224 piksel untuk memastikan dimensi input yang seragam bagi model CNN; Normalisasi—nilai piksel dinormalisasi ke dalam rentang 0–1 guna mempercepat proses pembelajaran dan meningkatkan stabilitas pelatihan; serta Augmentasi Data—teknik seperti rotasi, pembalikan horizontal, zoom, dan penyesuaian kecerahan diterapkan untuk meningkatkan keragaman data dan mengurangi overfitting. Mengingat terbatasnya jumlah citra yang tersedia, metode Stratified 5-Fold Cross-Validation digunakan sebagai pengganti pembagian train-test tunggal. Sebanyak 92 citra tersebut dibagi menjadi lima fold secara berstrata dengan tetap mempertahankan distribusi kelas. Pada setiap iterasi, empat fold digunakan untuk pelatihan dan satu fold digunakan untuk validasi. Proses ini diulangi sebanyak lima kali sehingga setiap citra digunakan satu kali sebagai data validasi. Augmentasi data secara online diterapkan hanya pada subset pelatihan untuk mencegah kebocoran data, di mana 80% data digunakan untuk pelatihan model dan 20% untuk evaluasi kinerja. Untuk meningkatkan keragaman data dan mengurangi risiko overfitting, augmentasi data secara online diterapkan pada citra pelatihan. Proses augmentasi dilakukan secara dinamis selama pelatihan model, bukan dengan membuat berkas citra tambahan secara permanen. Transformasi yang diterapkan meliputi rotasi citra, pembalikan horizontal, zoom, dan variasi kecerahan. Transformasi ini menghasilkan representasi citra yang berbeda di setiap iterasi pelatihan sembari mempertahankan ukuran dataset asli sebanyak 92 citra. Dengan 73 citra dalam subset pelatihan, ukuran batch sebesar 8, dan 25 epoch, prosedur pelatihan tersebut menghasilkan 2.000 paparan citra efektif.

2.4 Arsitektur model CNN

Arsitektur CNN yang diusulkan menerima citra RGB dengan ukuran input 224 × 224 × 3. Lapisan konvolusi pertama terdiri dari 32 filter dengan kernel 3 × 3, diikuti oleh fungsi aktivasi ReLU dan lapisan MaxPooling 2 × 2. Lapisan konvolusi kedua menggunakan 64 filter (3 × 3) yang diikuti oleh aktivasi ReLU dan MaxPooling. Lapisan konvolusi ketiga memuat 128 filter (3 × 3) dengan aktivasi ReLU dan MaxPooling. Peta fitur yang diekstraksi kemudian diratakan (*flattened*) dan dihubungkan ke lapisan *fully connected* yang berisi 128 neuron dengan aktivasi ReLU. Lapisan Dropout (0,5) diterapkan untuk mengurangi *overfitting* sebelum mencapai lapisan keluaran. Terakhir, lapisan Dense dengan 4 neuron dan aktivasi Softmax digunakan untuk mengklasifikasikan keempat kategori limbah (plastik, kertas, kaca, dan logam). Arsitektur ini memiliki sekitar 11.169.476 parameter yang dapat dilatih.

2.4.1 Lapisan masukan

2.5.1

Citra masukan diubah ukurannya menjadi 224 × 224 piksel dengan tiga kanal warna RGB. Oleh karena itu, tensor masukan dari CNN yang diusulkan ditetapkan sebesar 224 × 224 × 3. Citra masukan dinormalisasi ke rentang nilai piksel 0 hingga 1 sebelum dimasukkan ke dalam jaringan.

2.4.2 Lapisan Konvolusi

Layer	Filters/Neurons	kernel	Activation
Conv2D-1	**32**	**3 x 3**	**ReLU**
Conv2D-2	**64**	**3 x 3**	**ReLU**
Conv2D-3	**128**	**3x 3**	**ReLU**

Tabel 3. Arsitektur CNN

Komponen ekstraksi fitur terdiri dari tiga lapisan konvolusi. Lapisan konvolusi pertama menggunakan 32 filter dengan kernel berukuran 3 × 3, diikuti oleh fungsi aktivasi ReLU. Lapisan konvolusi kedua meningkatkan jumlah filter menjadi 64, sedangkan lapisan konvolusi ketiga menggunakan 128 filter. Semua lapisan konvolusi menggunakan kernel 3 × 3 dan aktivasi ReLU untuk mengekstrak fitur visual hierarkis dari citra masukan.

2.4.3 Pooling Layers

Each convolutional layer is followed by a 2 × 2 max-pooling operation. Max pooling is used to reduce the spatial dimensions of the feature maps while retaining the most prominent features. This operation also helps reduce the computational complexity of the subsequent layers.

2.4.4 Fully Connected and Output Layers

After the convolutional and pooling operations, the resulting feature maps are flattened into a one-dimensional vector using a flattening layer. The flattened features are then passed to a fully connected layer containing 128 neurons with ReLU activation. A dropout layer with a rate of 0.5 is applied to reduce the risk of overfitting. Finally, the output layer contains four neurons corresponding to the four waste categories and uses the softmax activation function to generate class probabilities.

2.4.5 Trainable Parameters

Total params: 11,169,476 (42.61 MB)

Trainable params: 11,169,476 (42.61 MB)

Non-trainable params: 0 (0.00 B)

The proposed CNN contains 11,169,476 total parameters, all of which are trainable. No non-trainable parameters are present because the proposed CNN is trained from scratch.

2.4.6 Tabel Arsitektur

Layer	Configuration	Actvation	Function
Input	224 × 224 × 3	–	Input image
Conv2D-1	32 filters, 3 × 3	ReLU	Feature extraction
MaxPooling-1	2 × 2	–	Downsampling
Conv2D-2	64 filters, 3 × 3	ReLU	Feature extraction
MaxPooling-2	2 × 2	–	Downsampling
Conv2D-3	128 filters, 3 × 3	ReLU	Feature extraction
MaxPooling-3	2 × 2	–	Downsampling

Flatten	–	–	Feature vector conversion
Dense	128 neurons	ReLU	Feature learning
Dropout	0.5	–	Regularization
Output	4 neurons	Softmax	Classification

Table 4. CNN Architecture

The proposed architecture contains three convolutional layers, three max-pooling layers, one fully connected layer, one dropout layer, and one output layer. The final classification layer consists of four neurons corresponding to plastic, paper, glass, and metal waste.

2.5 Model Evaluation

The performance of the CNN model was evaluated using several classification metrics, namely accuracy, precision, recall, and F1-score. These metrics were calculated based on the confusion matrix generated during testing. Accuracy was used to measure the overall correctness of the classification model and is defined as: Accuracy = (TP + TN) / (TP + TN + FP + FN) (1), Precision measures the proportion of correctly predicted positive instances: Precision = TP / (TP + FP) (2), Recall measures the ability of the model to identify all relevant instances: Recall = TP / (TP + FN) (3), The F1-score represents the harmonic mean of precision and recall: F1-Score = 2 × (Precision × Recall) / (Precision + Recall) (4), where TP denotes True Positive, TN denotes True Negative, FP denotes False Positive, and FN denotes False Negative. In addition to these metrics, a confusion matrix was used to analyze the distribution of classification results and identify potential misclassification among waste categories. The best-performing model was selected based on the highest accuracy value while maintaining balanced precision, recall, and F1-score values.

III. Hasil dan Pembahasan

3.1 Effect of Epoch on Model Performance

The first experiment was conducted to analyze the effect of the number of epochs on the performance of the CNN model. The evaluation metrics used were accuracy, precision, recall, and F1-score. The results are presented in Table 5 and figure 2. The initial evaluation using a single 80:20 train-test split produced an accuracy of 97%. However, this result should be interpreted with caution because the test set consisted of only 19 images. With such a small test set, a small number of correctly or incorrectly classified samples can substantially affect the reported accuracy. Therefore, the 97% accuracy obtained from the single split may not fully represent the model's generalization capability.

no	Jumlah gambar	epoch	Batch size	Learning rate	akurasi	precision	recall	F1-score
1	92	1	8	1e-4	0,40	0,41	0,40	0,34
2	92	3	8	1e-4	0,67	0,76	0,67	0,68
3	92	5	8	1e-4	0,83	0,84	0,83	0,83
4	92	7	8	1e-4	0,89	0,89	0,89	0,89
5	92	9	8	1e-4	0,91	0,92	0,91	0,91
6	92	11	8	1e-4	0,91	0,92	0,91	0,91
7	92	13	8	1e-4	0,91	0,92	0,91	0,91
8	92	15	8	1e-4	0,95	0,96	0,95	0,95
9	92	17	8	1e-4	0,95	0,96	0,95	0,95
10	92	20	8	1e-4	0,97	0,97	0,97	0,97

Table 5. Effect of Epoch on CNN Performance

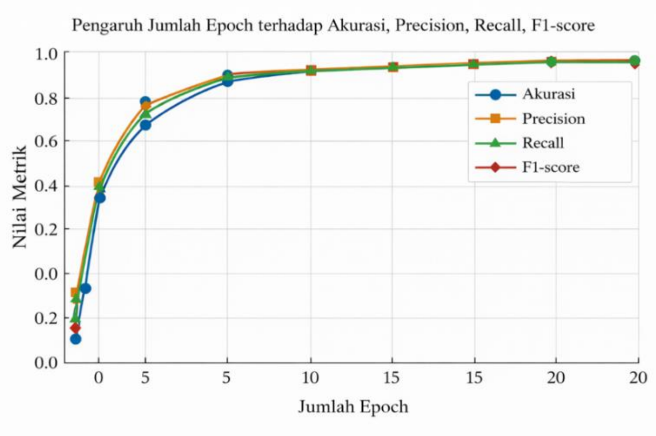

Figure 2. Graph of the Increase in Accuracy, Precision, Recall, and F1-Score with the Addition of Epochs

Table 2 shows the influence of epoch variation on CNN performance. The results indicate that increasing the number of epochs improves classification performance during the early training phase because the model gradually learns discriminative features from waste images. However, after reaching a certain number of epochs, the performance improvement becomes relatively stable, indicating that the model has reached convergence. The best performance was obtained at the optimal epoch configuration, where the model achieved the highest accuracy, precision, recall, and F1-score. Nevertheless, excessive training epochs may increase the possibility of overfitting, especially considering the limited dataset size used in this study.

3.2 Effect of Batch Size on Model Performance

The second experiment evaluated the impact of batch size on CNN classification performance. Various batch sizes ranging from 2 to 20 were tested while maintaining the other parameters constant. The initial evaluation using a single 80:20 train-test split produced an accuracy of 97%. However, this result should be interpreted with caution because the test set consisted of only 19 images. With such a small test set, a small number of correctly or incorrectly classified samples can substantially affect the reported accuracy. Therefore, the 97% accuracy obtained from the single split may not fully represent the model's generalization capability.

no	Jumlah gambar	epoch	Batch size	Learning rate	akurasi	precision	recall	F1-score
1	92	25	2	1e-4	0,91	0,91	0,91	0,91
2	92	25	4	1e-4	0,95	0,95	0,95	0,95
3	92	25	6	1e-4	0,95	0,96	0,95	0,95
4	92	25	8	1e-4	0,97	0,97	0,97	0,97
5	92	25	10	1e-4	0,95	0,95	0,95	0,95
6	92	25	12	1e-4	0,95	0,95	0,95	0,95
7	92	25	14	1e-4	0,96	0,97	0,96	0,96
8	92	25	16	1e-4	0,95	0,96	0,95	0,95
9	92	25	18	1e-4	0,91	0,92	0,91	0,91
10	92	25	20	1e-4	0,94	0,94	0,94	0,94

Table 6. Effect of Batch Size on CNN Performance

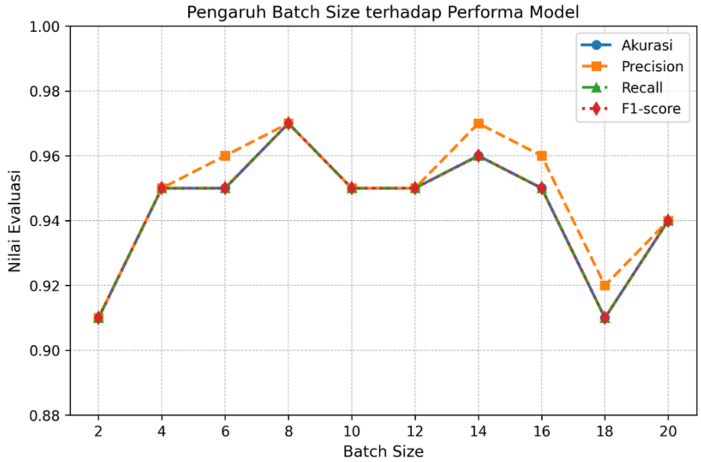

Figure 3. Graph of Accuracy, Precision, Recall, and F1-Score Evaluation Based on Batch Size Variations

The batch size experiment demonstrates that different batch configurations influence the stability and accuracy of the CNN training process. A smaller batch size allows the model to update weights more frequently, which may improve feature learning on a limited dataset. However, extremely small batch sizes can increase training instability. Based on the experimental results, the selected batch size achieved the highest evaluation performance. This configuration provided a suitable balance between learning stability and computational efficiency.

3.3 Effect of Learning Rate on Model Performance

The third experiment investigated the influence of learning rate on CNN training performance. Several learning rate values ranging from 1×10^{-1} to 1×10^{-20} were evaluated.

no	Jumlah gambar	epoch	Batch size	Learning rate	akurasi	precision	recall	F1-score
1	92	25	20	1e-1	0,35	0,34	0,35	0,27
2	92	25	20	1e-3	0,90	0,92	0,90	0,90
3	92	25	20	1e-5	0,73	0,74	0,73	0,73
4	92	25	20	1e-7	0,32	0,32	0,32	0,28
5	92	25	20	1e-9	0,31	0,31	0,31	0,27

Table 7. Effect of Learning Rate on CNN Performance

Preliminary experiments with learning rates below 1e-5 (1e-7 to 1e-20) consistently resulted in accuracy of approximately 0.31–0.32, which is close to the random-guessing baseline for the four-class classification task. Therefore, these values were excluded from the main analysis because they did not provide meaningful performance variation and indicated insufficient convergence within the given training budget.

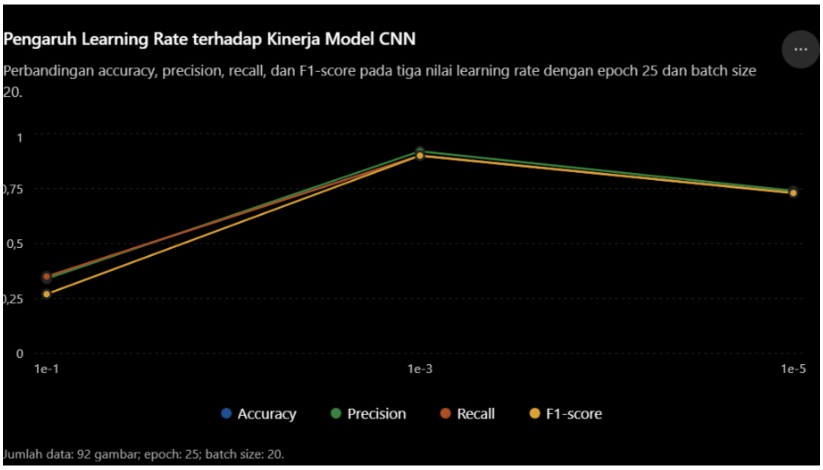

Figure 4. Evaluation Graph of Accuracy, Precision, Recall, and F1-Score at Various Learning Rate Values

The learning rate experiment shows that optimization performance is highly dependent on the selected learning rate value. A high learning rate may cause unstable updates and prevent the model from reaching optimal convergence, while an excessively small learning rate may slow the learning process and result in insufficient feature optimization. The selected learning rate provided the best balance between convergence speed and classification performance. These results indicate that proper hyperparameter selection is essential, particularly when training CNN models using limited image datasets, The learning rate search was restricted to the range of 1e-1 to 1e-5, consistent with commonly reported effective ranges for small CNNs trained with Adam-family optimizers. Values below 1e-5 were excluded after preliminary tests confirmed that they prevented meaningful convergence within the training budget.

3.4 Results of Stratified 5-Fold Cross-Validation

Fold	Training	Validation	Accuracy	Precision	Recall	F1-Score
Fold 1	73	19	0.368421	0.502924	0.368421	0.345990
Fold 2	73	19	0.210526	0.257519	0.210526	0.210223
Fold 3	74	18	0.333333	0.273810	0.333333	0.290965
Fold 4	74	18	0.333333	0.266667	0.333333	0.293827
Fold 5	74	18	0.388889	0.375000	0.388889	0.367725
Mean	—	—	0.326901	0.335184	0.326901	0.301746
Std. Dev.	—	—	0.069268	0.105137	0.069268	0.060964

Table 8. Stratified 5-Fold Cross-Validation Results

Table 8 presents the results of the Stratified 5-Fold Cross-Validation performed on the dataset consisting of 92 images. The dataset was divided into five folds while maintaining the class distribution in each fold. In each iteration, one fold was used as the validation set, while the remaining four folds were used for training. The number of training samples ranged from 73 to 74 images, while the validation samples ranged from 18 to 19 images. The results show that the model performance varied across the five folds. Fold 1 achieved an accuracy of 36.84%, precision of 50.29%, recall of 36.84%, and F1-score of 34.60%. Fold 2 produced the lowest performance, with an accuracy of 21.05%, precision of 25.75%, recall of 21.05%, and F1-score of 21.02%. Fold 3 and Fold 4 obtained an accuracy of 33.33%, with F1-scores of 29.10% and 29.38%, respectively. Fold 5 achieved the highest accuracy of 38.89%, with a precision of 37.50%, recall of 38.89%, and F1-score of 36.77%. Overall, the model obtained a mean accuracy of 32.69% ± 6.93%, precision of 33.52% ± 10.51%, recall of 32.69% ± 6.93%, and F1-score of 30.17% ± 6.10%. The variation in performance across folds indicates that the model's predictive performance is sensitive to the composition of the training and validation subsets. This variation is particularly relevant given the limited dataset size of only 92 images. For a four-class classification problem, the theoretical accuracy of random guessing is approximately 25%. Therefore, the mean accuracy of 32.69% indicates that the model performs above the random baseline, but its generalization performance remains limited. These findings suggest that the small dataset size may restrict the model's ability to learn representative features and generalize consistently to unseen samples. Consequently, a larger and more diverse dataset, together with further evaluation using transfer learning architectures, is recommended for future research. To obtain a more reliable estimate of model generalization, stratified 5-fold cross-validation was subsequently performed. In contrast to the single 80:20 split, cross-validation evaluates the model across multiple training and validation subsets. The proposed CNN achieved a mean accuracy of 32.69% ± 6.93% across the five folds. The substantially lower performance compared with the 97% accuracy obtained from the single split indicates that the earlier result may have been influenced by the limited size and composition of the test set, suggesting possible overfitting.

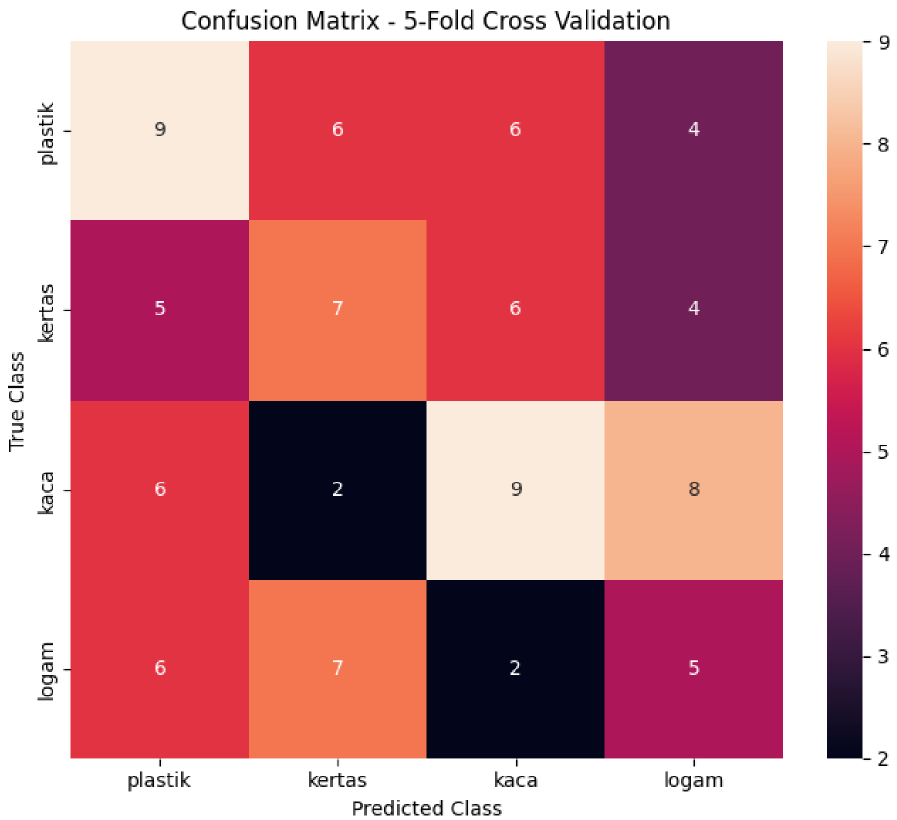

Figure 5. Aggregated Confusion Matrix from 5-Fold Cross-Validation

Figure 5 presents the aggregated confusion matrix obtained from the Stratified 5-Fold Cross-Validation for the four waste categories: plastic, paper, glass, and metal. The rows represent the actual classes, while the columns represent the predicted classes. The diagonal values indicate correctly classified samples, whereas the off-diagonal values represent misclassified samples. The model correctly classified 9 plastic images, 7 paper images, 9 glass images, and 5 metal images. Therefore, 30 out of 92 validation samples were correctly classified, corresponding to an overall accuracy of approximately 32.61%. The relatively low number of correct predictions indicates that the model still has difficulty distinguishing among the four waste categories. For the plastic class, 9 samples were correctly classified, while 6 samples were incorrectly predicted as paper, 6 as glass, and 4 as metal. For the paper class, 7 samples were correctly classified, whereas 5 were predicted as plastic, 6 as glass, and 4 as metal. The glass class achieved 9 correct predictions; however, 6 samples were classified as plastic, 2 as paper, and 8 as metal. The metal class obtained 5 correct predictions, while 6 samples were predicted as plastic, 7 as paper, and 2 as glass. The largest misclassification occurred between the glass and metal classes, where 8 glass samples were predicted as metal. In addition, plastic was frequently misclassified as paper and glass, with 6 samples for each category. These results indicate that the visual characteristics of several waste categories may overlap, making classification difficult for a CNN trained with a limited number of images. The class-wise results also show relatively low recognition rates. Based on the confusion matrix, the recall values are approximately 36.00% for plastic, 31.82% for paper, 36.00% for glass, and 25.00% for metal. Metal obtained the lowest recall, indicating that this class was the most difficult for the model to identify correctly. These findings are consistent with the cross-validation results presented in Table 8, where the mean accuracy was 32.69% and the mean F1-score was 30.17%. Overall, the confusion matrix demonstrates that the model has limited generalization capability across the four waste categories. The results are likely influenced by the small dataset size of 92 images, which limits the diversity of visual characteristics available during training. Therefore, increasing the dataset size, improving data diversity, and evaluating transfer learning architectures may help improve the classification performance in future studies.

3.5 Confirmation Experiment Using the Selected Hyperparameter Configuration

Based on the sequential one-factor-at-a-time (OFAT) tuning experiments, the best-performing values for each hyperparameter were identified individually. The selected configuration consisted of 20 epochs, a batch size of 8, and a learning rate of 1×10^{-3}. A confirmation experiment was then conducted by combining these selected values into a single configuration and retraining the CNN model. The purpose of this experiment was to verify the performance of the final configuration obtained from the sequential OFAT tuning process. The results of the confirmation experiment are presented. The configuration of 20 epochs, batch size of 8, and learning rate of 1×10^{-3} achieved the best performance among the configurations evaluated during the sequential tuning process. However, because the hyperparameters were tuned sequentially rather than simultaneously, this configuration should not be interpreted as the globally optimal combination across all possible hyperparameter settings.

3.6 Discussion

This study employed a sequential one-factor-at-a-time (OFAT) tuning strategy rather than a joint grid search; therefore, the reported configuration should be interpreted as a locally optimal rather than globally optimal setting. A confirmation experiment was then conducted by combining these selected values into a single configuration and retraining the CNN model. The purpose of this experiment was to verify the performance of the final configuration obtained from the sequential OFAT tuning process. The results of the confirmation experiment . The configuration of 20 epochs, batch size of 8, and learning rate of 1×10^{-3} achieved the best performance among the configurations evaluated during the sequential tuning process. However, because the hyperparameters were tuned sequentially rather than simultaneously, this configuration should not be interpreted as the globally optimal combination across all possible hyperparameter settings.The obtained accuracy of 97% indicates that the proposed CNN model achieved promising performance for household waste image classification. However, direct comparison with previous studies should be interpreted carefully because differences exist in dataset size, number of waste categories, image characteristics, and experimental settings. Although the proposed model achieved a high accuracy value, the evaluation dataset used in this study is relatively limited compared with several previous studies. [5][10]The high performance may be influenced by the controlled image acquisition environment and the characteristics of the collected household waste images.[9][11] Therefore, the obtained accuracy should be considered as an initial evaluation of model feasibility rather than evidence that the proposed model universally outperforms previous approaches. Nevertheless, the results demonstrate that CNN can effectively extract visual features from household waste images and provide accurate classification results for the tested categories. Future studies should evaluate the model using larger and more diverse datasets containing variations in lighting conditions, backgrounds, camera devices, and real-world household environments.The selection of a CNN architecture trained from scratch in this study was based on the objective of developing a lightweight and interpretable model architecture specifically designed for household waste classification. The proposed CNN was developed using a relatively simple architecture to evaluate the feasibility of extracting waste-related visual features from the collected household waste images. However, we acknowledge that transfer learning approaches, including MobileNet, ResNet, EfficientNet, and Vision Transformer (ViT), are widely adopted for small-scale image classification tasks because pre-trained models can utilize previously learned feature representations from large-scale datasets such as ImageNet. These approaches may provide better generalization, particularly when the available training dataset is limited. Therefore, the obtained accuracy of 97% should not be interpreted as evidence that the proposed CNN architecture outperforms transfer learning-based methods. Instead, the result demonstrates the feasibility of applying a custom CNN model for the evaluated household waste dataset. A comprehensive comparison with transfer learning architectures will be conducted in future research to determine the optimal model for household waste classification. The Stratified 5-Fold Cross-Validation results indicate that the proposed CNN achieved an average accuracy with a standard deviation The relatively small standard deviation indicates that the model performance remained relatively consistent across the five folds. However, the limited dataset size of 92 images remains a constraint and may affect the generalization capability of the model. The substantial difference between the accuracy obtained from the single train-test split and the stratified 5-fold cross-validation requires careful consideration. The proposed CNN achieved 97% accuracy under the single 80:20 split, whereas its mean accuracy decreased to 32.69% ± 6.93% under stratified 5-fold cross-validation. The model also obtained an accuracy of 33.33% in the transfer learning comparison. These differences are primarily associated with the limited dataset size, which consists of only 92 original images. In the single-split experiment, only 19 images were used for testing, making the accuracy highly sensitive to the specific composition of the test set. Consequently, the 97% accuracy may represent an optimistic estimate of model performance and may be affected by overfitting to the training data. In contrast, stratified 5-fold cross-validation evaluates the model across multiple subsets and therefore provides a more robust indication of its generalization capability. The substantially lower cross-validation performance suggests that the model has difficulty generalizing to unseen samples. Therefore, the 97% accuracy obtained from the single-split experiment should not be considered the primary indicator of the proposed model's performance. The cross-validation results are considered more appropriate for assessing generalization given the limited dataset size.

3.7 Comparison with Transfer Learning Models

Model	Accuracy	Precision	Recall	F1-score
Proposed CNN	0.333333	0.189899	0.333333	0.237654
MobileNetV2	0.777778	0.777778	0.777778	0.773449
ResNet50	0.777778	0.782407	0.777778	0.767725
EfficientNetB0	0.888889	0.909259	0.888889	0.887446

Table 9. Performance Comparison of CNN and Transfer Learning Models

The performance comparison between the proposed CNN and the transfer learning models is presented in Table 9. The proposed CNN achieved an accuracy of 33.33%, while MobileNetV2, ResNet50, and EfficientNetB0 achieved accuracies of 77.78%, 77.78%, and 88.89%, respectively. These results indicate that EfficientNetB0 achieved the best classification performance among the evaluated models, whereas the proposed CNN obtained the lowest accuracy. This finding suggests that pretrained transfer learning architectures can provide more effective feature representations and better generalization than a CNN trained from scratch when using a limited dataset. The results in Table 9 should also be interpreted in the context of the evaluation protocol. The proposed CNN achieved 33.33% accuracy in the transfer learning comparison, which is substantially lower than the 97% accuracy obtained using the initial single 80:20 train-test split. This difference indicates that the performance of the proposed CNN is highly sensitive to dataset partitioning and the evaluation procedure. Therefore, the results obtained from different evaluation protocols should not be directly compared unless the same dataset partitioning and evaluation procedure are applied. For a fair comparison, all evaluated architectures were assessed using the same dataset split and evaluation procedure.

3.8 Overfitting Analysis

Training accuracy vs validation accuracy

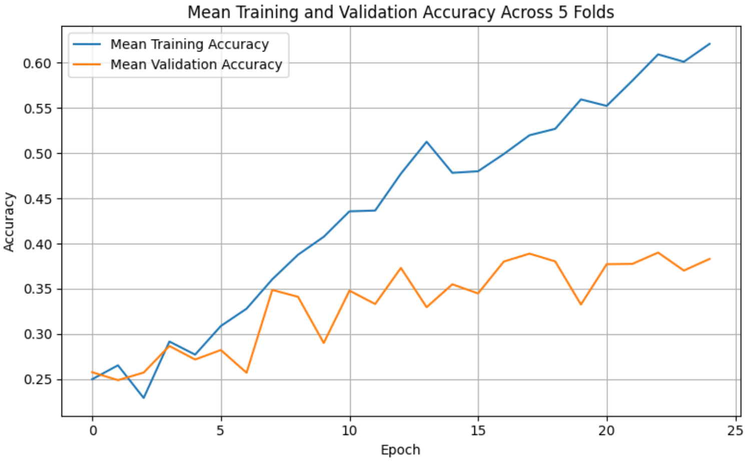

Figure 6. Mean Training and Validation Accuracy Across 5 Folds

The training and validation accuracy curves were analyzed to evaluate the learning behavior and generalization capability of the proposed CNN model. Training accuracy represents the classification performance of the model on the training data, whereas validation accuracy represents its performance on previously unseen validation data. As shown in Figure 6, the training accuracy generally increases as the number of epochs increases, indicating that the model progressively learns the visual features of the waste categories. The validation accuracy also shows an increasing trend, although fluctuations between epochs may occur due to the relatively small dataset used in this study. The difference between training and validation accuracy is used as an indication of the generalization gap. A relatively small gap between the two curves indicates that the model can generalize its learned features to validation data. Conversely, if the training accuracy continues to increase while the validation accuracy stagnates or decreases, this indicates a potential overfitting problem. Therefore, the training and validation accuracy curves provide an important basis for evaluating whether the model learns general patterns rather than memorizing the training images.

Training loss vs validation loss

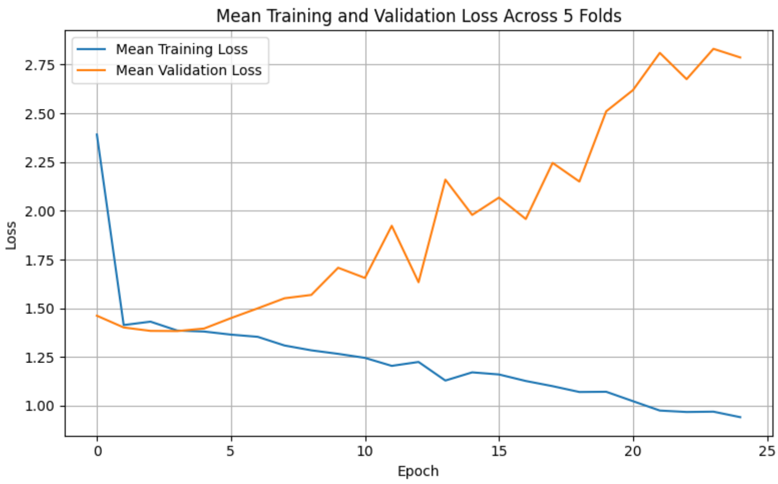

Figure 7. Mean Training and Validation Loss Across 5 Folds

The training and validation loss curves were further examined to identify potential overfitting during the model training process. Training loss measures the error produced by the model on the training data, while validation loss measures the error on the validation data. As illustrated in Figure 7, the training loss generally decreases throughout the training process, indicating that the model progressively minimizes the classification error on the training data. The validation loss is also evaluated to determine whether the reduction in training error is accompanied by improved generalization to unseen data. When both training and validation loss decrease simultaneously, the model demonstrates a stable learning process. However, an increasing validation loss while training loss continues to decrease indicates that the model may be learning specific characteristics of the training data rather than generalizable features. This condition is commonly interpreted as an indication of overfitting. The loss curves are therefore considered together with the accuracy curves to provide a more reliable assessment of the model's generalization capability.

Overfitting Analysis

The training and validation curves indicate a potential overfitting tendency in the later training epochs. The training accuracy continues to increase while the improvement in validation accuracy becomes limited. At the same time, the training loss continues to decrease, whereas the validation loss tends to increase or fluctuate at a higher level. This behavior suggests that the CNN model increasingly fits the training samples but does not obtain a proportional improvement in its ability to generalize to unseen validation samples. The observed generalization gap is particularly relevant because the dataset contains a relatively limited number of images. Therefore, the high training performance should not be interpreted solely as evidence of strong generalization. The use of five-fold cross-validation provides additional evaluation across different training and validation subsets. Nevertheless, the observed differences between training and validation performance indicate that the model should be interpreted with consideration of the limited dataset size.

3.9 Performance Metrics Comparison

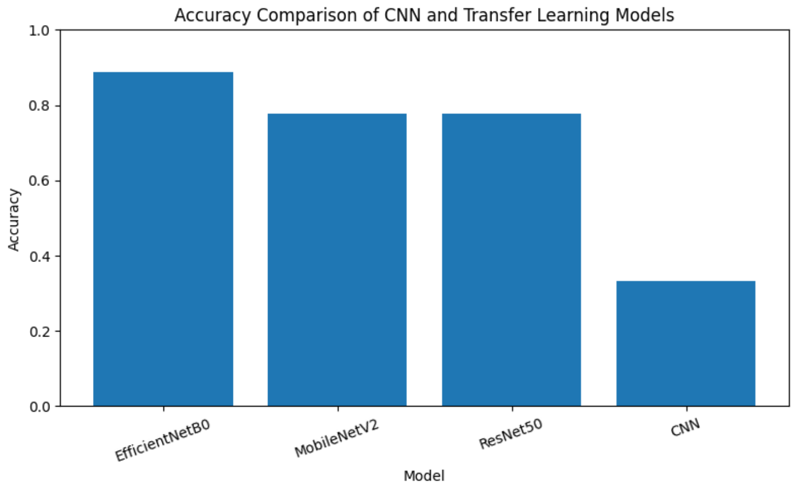

Figure 8. Accuracy Comparison of CNN and Transfer Learning Models

Figure 8 illustrates the accuracy performance comparison across all evaluated models. The results demonstrate that EfficientNetB0 achieved the highest accuracy at approximately 89% (0.89), outperforming all other architectures. Both MobileNetV2 and ResNet50 exhibited moderate and identical accuracy levels of around 78% (0.78). In contrast, the baseline CNN model registered the lowest accuracy, reaching only 33% (0.33). This significant performance gap highlights the strong capability of transfer learning models in correctly classifying overall instances compared to a standard, non-pretrained CNN.

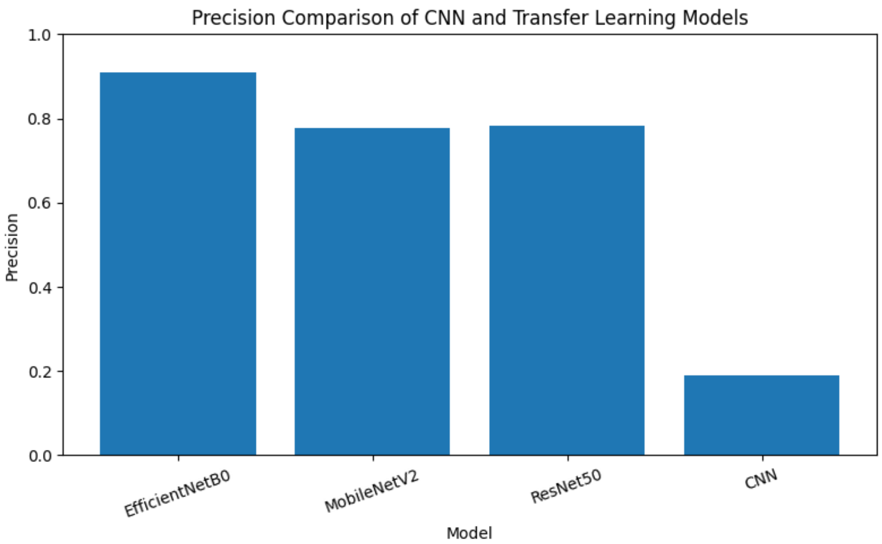

Figure 9. Precision Comparison of CNN and Transfer Learning Models

Figure 9 highlights the precision performance of the models, measuring the exactness of positive predictions. EfficientNetB0 leads with the highest precision score of approximately 91% (0.91), indicating a low rate of false-positive classifications. MobileNetV2 and ResNet50 showed comparable precision scores, reaching around 78% (0.78). Meanwhile, the standard CNN model performed poorly, obtaining a precision score of less than 20% (~0.19). These results confirm that transfer learning significantly minimizes misclassification errors in positive predictions.

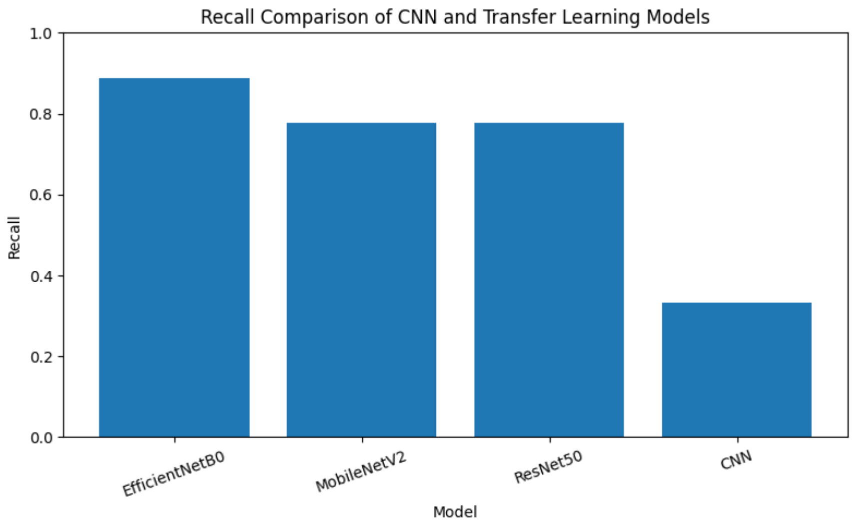

Figure 10. Recall Comparison of CNN and Transfer Learning Models

Figure 10 displays the recall (sensitivity) comparison, which measures each model's ability to identify all relevant positive instances. EfficientNetB0 achieved the top recall score at approximately 89% (0.89). Both MobileNetV2 and ResNet50 followed closely with identical recall values of 78% (0.78). Conversely, the standard CNN architecture struggled significantly, achieving a recall of only 33% (0.33). The high recall achieved by EfficientNetB0 confirms its effectiveness in minimizing false negatives during detection.

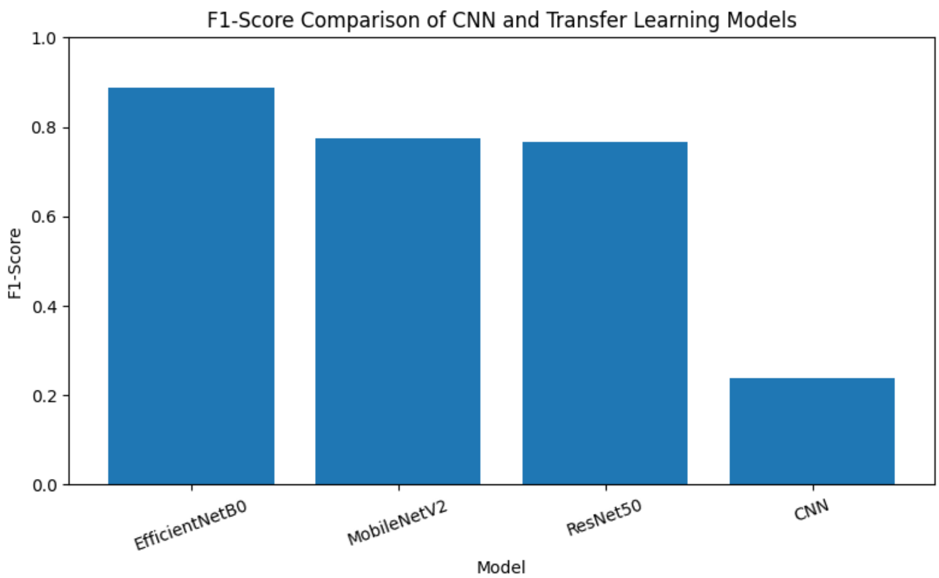

Figure 11. F1-Score Comparison of CNN and Transfer Learning Models

Figure 11 presents the F1-Score comparison, representing the harmonic mean of precision and recall to evaluate overall balanced performance. EfficientNetB0 attained the highest F1-Score at approximately 89% (0.89), demonstrating superior stability and balance between precision and sensitivity. MobileNetV2 and ResNet50 achieved nearly identical scores of 78% (0.78) and 77% (0.77), respectively. Finally, the baseline CNN model recorded a low F1-Score of 24% (0.24), further proving that transfer learning is far more robust for this task.

IV. Conclusions and Future Works

This research successfully developed a CNN-based household waste image classification model capable of automatically identifying different waste categories from image data. The developed model achieved satisfactory classification performance based on accuracy, precision, recall, and F1-score evaluation. Furthermore, the trained model was integrated into a simple web-based application that enables users to upload waste images and obtain automatic classification results. However, the current implementation is still limited to image-based identification and has not yet supported real-time camera detection or deployment on edge devices. Future research can focus on developing real-time waste detection systems using mobile devices or embedded platforms. The proposed system was designed to classify four categories of inorganic waste, namely plastic, paper, glass, and metal, using digital image data. Experimental results demonstrated that CNN is highly effective in recognizing and classifying waste objects based on their visual characteristics, including shape, texture, and color. The implementation of preprocessing techniques such as image resizing, normalization, and data augmentation contributed significantly to improving data quality and enhancing model performance during the training process. The evaluation results revealed that training parameters play a crucial role in determining the effectiveness of the CNN model. Among the tested configurations, the optimal performance was achieved using 20 epochs, a batch size of 8, and a learning rate of 1×10^{-3}. Under these conditions, the model obtained a classification accuracy of 97%, accompanied by high and balanced precision, recall, and F1-score values .The experimental results demonstrate that the proposed CNN can perform waste image classification; however, its generalization capability is limited by the small dataset size. Although an accuracy of 97% was obtained using a single 80:20 train-test split, stratified 5-fold cross-validation resulted in a mean accuracy of 32.69% ± 6.93%. The substantial difference between these results suggests that the single-split accuracy may provide an optimistic estimate of model performance and may be affected by overfitting. Therefore, the cross-validation result provides a more reliable indication of the model's generalization capability. These findings highlight the importance of using robust validation strategies when developing CNN-based classification models with limited datasets. Future studies should increase the number and diversity of real-world waste images and investigate more robust architectures and regularization techniques to improve generalization performance. These findings indicate that proper hyperparameter optimization can significantly improve model convergence, reduce classification errors, and enhance the overall reliability of the waste identification system. Furthermore, the developed system has the potential to support household waste management by assisting users in sorting waste automatically and accurately. The ability to identify waste categories in real time can contribute to increasing public awareness of waste segregation practices, promoting recycling activities, and reducing environmental pollution. Therefore, the proposed system can serve as an intelligent technological solution for supporting sustainable waste management in household environments. Despite the promising results, this study has several limitations. The dataset used consisted of only 92 images and was limited to four categories of inorganic waste. Consequently, the model may not fully represent the diversity of waste objects encountered in real-world environments. Future research should consider utilizing larger and more diverse datasets, including organic waste and residual waste categories, to improve model generalization capabilities. In addition, more advanced Deep Learning architectures such as MobileNet, ResNet, EfficientNet, or Vision Transformer (ViT) can be explored and compared to achieve higher classification performance. Future studies may also focus on integrating the model into web-based or mobile applications, enabling direct implementation by households and supporting the development of smart waste management systems in real-world environments. Based on Stratified 5-Fold Cross-Validation, the proposed CNN achieved an average accuracy of 32.69% ± 6.93% with a precision of 33.52% ± 10.51%, recall of 32.69% ± 6.93%, and F1-score of 30.17% ± 6.10%.

V. Panduan Penulisan Persamaan

Dalam penelitian ini, persamaan matematika digunakan untuk menjelaskan proses utama pada Convolutional Neural Network (CNN), meliputi konvolusi, fungsi aktivasi, pooling, normalisasi, dan perhitungan metrik evaluasi. Setiap persamaan diberi nomor secara berurutan dan ditempatkan di sisi kanan persamaan.

1. Persamaan Convolution

Proses konvolusi digunakan untuk mengekstraksi fitur dari citra masukan. Persamaan konvolusi dapat dituliskan sebagai:

$$Z_{i,j,k} = \sum_{m}\sum_{n}\sum_{c} X_{i+m,j+n,c}\, K_{m,n,c,k} + b_k \qquad (1)$$

Keterangan:

- $Z_{i,j,k}$= nilai feature map pada posisi (i, j)untuk filter ke-k
- X= citra atau feature map masukan
- K= kernel/filter konvolusi
- m, n= posisi kernel
- c= indeks channel
- b_k= bias filter ke-k

Persamaan ini menunjukkan bahwa CNN melakukan perkalian antara nilai piksel/fitur dengan kernel untuk menghasilkan feature map.

2. Fungsi Aktivasi ReLU

Setelah proses konvolusi, digunakan fungsi aktivasi Rectified Linear Unit (ReLU) untuk memberikan sifat non-linear pada jaringan.

$$f(x) = \max(0, x) \qquad (2)$$

Keterangan:

- x= nilai masukan dari hasil konvolusi
- $f(x)$= nilai keluaran fungsi ReLU

Jika nilai $x$negatif, maka hasilnya menjadi 0. Jika nilai $x$positif, nilainya tetap.

3. Max Pooling

Max pooling digunakan untuk mengurangi ukuran feature map sekaligus mempertahankan fitur yang paling dominan.

$$P_{i,j,k} = \max_{(m,n)\in R} Z_{i+m,j+n,k} \qquad (3)$$

Keterangan:

- $P_{i,j,k}$= hasil max pooling
- Z= feature map hasil konvolusi
- R= area pooling
- m, n= posisi dalam area pooling

Dalam implementasi CNN, misalnya digunakan MaxPooling dengan ukuran 2×2, maka nilai terbesar dari setiap area 2×2 akan dipertahankan.

4. Flatten

Layer flatten digunakan untuk mengubah feature map multidimensi menjadi vektor satu dimensi sebelum masuk ke fully connected layer.

$$F = \text{Flatten}(P) \qquad (4)$$

Jika feature map memiliki ukuran $H \times W \times C$, maka jumlah elemen setelah flatten adalah:

$$N = H \times W \times C \qquad (5)$$

Keterangan:

- H= tinggi feature map
- W= lebar feature map
- C= jumlah channel
- N= jumlah neuron hasil flatten

5. Fully Connected Layer

Pada fully connected layer, setiap neuron menerima masukan dari seluruh neuron pada layer sebelumnya.

$$y = Wx + b \qquad (6)$$

Keterangan:

- y= keluaran layer
- W= matriks bobot
- x= vektor masukan
- b= bias

6. Fungsi Aktivasi Softmax

Untuk klasifikasi jenis sampah, fungsi Softmax dapat digunakan pada layer output untuk menghasilkan probabilitas setiap kelas.

$$P(y = i \mid x) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \qquad (7)$$

Keterangan:

- $P(y = i \mid x)$= probabilitas citra termasuk kelas i
- z_i= nilai logit untuk kelas i

- C= jumlah kelas
- j= indeks kelas

Pada penelitian ini, jika terdapat empat kelas, maka Softmax menghasilkan empat nilai probabilitas, misalnya:

- Plastic
- Paper
- Glass
- Metal

Kelas dengan nilai probabilitas terbesar dipilih sebagai hasil prediksi.

7. Categorical Cross-Entropy

Fungsi loss yang dapat digunakan untuk klasifikasi multi-kelas adalah Categorical Cross-Entropy.

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \qquad (8)$$

Keterangan:

- L= nilai loss
- C= jumlah kelas
- y_i= label sebenarnya
- $\hat{y}_i$= probabilitas prediksi model untuk kelas i

Semakin kecil nilai loss, semakin dekat prediksi model terhadap label sebenarnya.

8. Accuracy

Akurasi digunakan untuk mengetahui persentase prediksi yang benar.

$$Accuracy = \frac{N_{correct}}{N_{total}} \times 100\% \qquad (9)$$

Keterangan:

- $N_{correct}$= jumlah prediksi yang benar
- N_{total}= jumlah seluruh data pengujian

9. Precision

Precision menunjukkan tingkat ketepatan model ketika memprediksi suatu kelas.

$$Precision = \frac{TP}{TP + FP} \qquad (10)$$

Keterangan:

- TP= True Positive
- FP= False Positive

10. Recall

Recall menunjukkan kemampuan model dalam menemukan seluruh data yang sebenarnya termasuk dalam suatu kelas.

$$Recall = \frac{TP}{TP + FN} \qquad (11)$$

Keterangan:

- TP= True Positive
- FN= False Negative

- 11. F1-Score

F1-score merupakan rata-rata harmonis antara precision dan recall.

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (12)$$

Nilai F1-score yang semakin mendekati 1 menunjukkan performa klasifikasi yang semakin baik.

VI. PANDUAN PENULISAN KUTIPAN/RUJUKAN DALAM TEKS ARTIKEL DAN DAFTAR REFERENSI

1. Sistem Kutipan yang Digunakan

Artikel menggunakan IEEE Reference Style. Setiap sumber yang digunakan dalam artikel diberi nomor berdasarkan urutan pertama kali sumber tersebut muncul di dalam teks.

Contoh:

Household waste classification using image processing and deep learning has received increasing attention in recent years [1].

Sumber pertama yang dikutip diberi nomor [1]. Sumber berikutnya diberi [2], kemudian [3], dan seterusnya.

Nomor tersebut tetap digunakan setiap kali sumber yang sama dikutip kembali.

Contoh:

Convolutional Neural Networks (CNNs) are widely used for image classification because they can automatically extract relevant visual features [1].

Kemudian pada paragraf berikutnya:

CNN-based approaches have also been applied to waste classification problems [1].

Tidak dibuat menjadi [2] karena sumbernya sama.

2. PENULISAN KUTIPAN SATU REFERENSI

Jika hanya menggunakan satu sumber, tuliskan nomor referensi dalam kurung siku.

Benar:

Deep learning has demonstrated strong performance in image classification tasks [1].

Salah:

Deep learning has demonstrated strong performance in image classification tasks (Author, 2024).

Salah:

Deep learning has demonstrated strong performance in image classification tasks [Author, 2024].

Dalam gaya IEEE, nomor referensi digunakan sebagai pengenal sumber, bukan nama belakang penulis dan tahun.

3. KUTIPAN DUA REFERENSI

Jika suatu pernyataan didukung oleh dua sumber, tuliskan nomor keduanya.

Contoh:

CNN and transfer learning approaches have been widely applied to image classification problems [2], [3].

Bukan:

CNN and transfer learning approaches have been widely applied to image classification problems [2–3].

Pedoman IEEE terbaru menyatakan bahwa rentang referensi ditulis sebagai nomor individual, misalnya [1], [2], [3], [4], bukan menggunakan rentang seperti [1]–[4].

4. Kutipan Beberapa Referensi

Jika terdapat beberapa sumber:

Several studies have investigated deep learning approaches for automatic waste classification [2], [4], [5], [7].

Jika sumbernya berurutan:

Several CNN-based methods have been proposed for image classification [3], [4], [5], [6].

Sebaiknya tetap mengikuti aturan jurnal tempat artikel dikirim, tetapi pedoman IEEE yang terbaru menyarankan nomor referensi dituliskan satu per satu.

5. Kutipan pada Awal Kalimat

Nama penulis boleh disebutkan apabila memang penting secara gramatikal atau untuk menekankan penelitian tertentu.

Contoh:

Smith [1] proposed a CNN-based approach for image classification.

Namun, jangan menulis:

According to Smith (2024) [1], CNN can be used for image classification.

Untuk gaya IEEE, tahun publikasi umumnya tidak digunakan sebagai bagian dari kutipan dalam teks.

Lebih baik:

CNN can be used for image classification [1].

6. Jika Nama Penulis Tidak Penting

Untuk artikel Anda, saya lebih menyarankan bentuk berikut:

Previous studies have demonstrated that CNN architectures can effectively extract spatial features from images [1], [2].

Daripada:

According to Simbolon et al. [1], CNN architectures can effectively extract spatial features from images.

Keduanya dapat digunakan, tetapi bentuk pertama lebih konsisten jika Anda ingin mengikuti pola IEEE yang menempatkan fokus pada temuan penelitian, bukan nama penulis. IEEE secara khusus menyarankan agar nama penulis tidak dimasukkan bersama nomor referensi kecuali nama tersebut memang menjadi bagian penting dari kalimat.

7. Posisi Nomor Kutipan

Nomor referensi diletakkan sebelum tanda baca akhir atau secara umum sebagai bagian dari kalimat sesuai aturan IEEE.

Contoh:

Image classification has become an important application of deep learning [1].

Bukan:

Image classification has become an important application of deep learning. [1]

Pedoman IEEE menyatakan bahwa referensi berada pada baris yang sama dan di dalam tanda kurung siku, terkait dengan tanda baca kalimat.

8. Contoh Kutipan untuk Artikel Anda

Untuk judul:

Development of a CNN-Based Household Waste Image Classification Model for Automatic Identification

contoh penulisan bagian pendahuluan:

The increasing volume of household waste has created significant challenges in waste management and environmental sustainability. Proper waste classification is important because different waste materials require different treatment and recycling processes [1]. However, manual waste classification can be time-consuming and may result in inconsistent classification. Recent developments in artificial intelligence have provided opportunities to automate waste classification using image-based approaches [2].

Convolutional Neural Networks (CNNs) have been widely used for image classification because they can automatically learn spatial features from input images [3]. CNN-based models have also been applied to waste classification by identifying visual characteristics such as shape, texture, and color [4], [5]. Transfer learning approaches using pretrained architectures such as MobileNetV2, ResNet50, and EfficientNetB0 can further improve classification performance, particularly when the available dataset is relatively limited [6], [7], [8].

Based on these considerations, this study develops a CNN-based household waste image classification model for automatic identification of waste categories. The proposed approach focuses on classifying household waste images into predefined categories based on their visual characteristics.

Perhatikan bahwa nama penulis dan tahun tidak perlu ditulis di dalam paragraf, sedangkan sumber ditunjukkan dengan nomor [1], [2], dan seterusnya.

9. Penulisan Daftar Referensi

Pada bagian akhir artikel dibuat bagian:

REFERENCES

Setiap sumber diberi nomor sesuai urutan kemunculannya dalam artikel.

Contoh:

[1] A. Author and B. Author, “Title of the article,” *Journal Name*, vol. 10, no. 2, pp. 100–110, 2024.

[2] C. Author, D. Author, and E. Author, “Deep learning for image classification,” *Journal Name*, vol. 5, no. 1, pp. 20–30, 2023.

[3] F. Author, “Convolutional neural networks for image recognition,” *Journal Name*, vol. 8, no. 3, pp. 50–60, 2022.

Dalam IEEE, nama depan penulis biasanya ditulis sebagai inisial, kemudian nama belakang.

10. FORMAT REFERENSI JURNAL

Format umum:

[Nomor] Inisial Nama Depan. Nama Belakang, “Judul artikel,” *Nama Jurnal*, vol. x, no. x, pp. xx–xx, tahun.

Contoh:

[1] A. B. Smith and C. D. Jones, “Deep learning for image classification,” *International Journal of Computer Science*, vol. 10, no. 2, pp. 100–108, 2024.

Perhatikan:

- Nomor menggunakan [ ]
- Nama penulis menggunakan inisial
- Judul artikel menggunakan tanda kutip
- Nama jurnal dicetak *italic*
- Volume ditulis vol.
- Nomor edisi ditulis no.
- Halaman ditulis pp.
- Tahun diletakkan di bagian akhir

11. FORMAT REFERENSI CONFERENCE/PROCEEDINGS

Format:

[2] A. B. Author, “Title of conference paper,” in *Proc. Name of Conference*, City, Country, 2024, pp. 100–105.

Contoh:

[2] R. Kumar and S. Singh, “Automatic waste classification using convolutional neural networks,” in *Proc. Int. Conf. Artificial Intelligence and Computer Vision*, Jakarta, Indonesia, 2024, pp. 120–125.

12. FORMAT REFERENSI BUKU

Format:

[3] A. B. Author, *Book Title*, xth ed. City, Country: Publisher, year.

Contoh:

[3] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.

13. Format Referensi Website

Untuk sumber dari website:

[4] Organization Name, "Title of webpage," Website Name. [Online]. Available: URL. [Accessed: Month Day, Year].

Contoh:

[4] World Health Organization, "Electronic waste and health," World Health Organization. [Online]. Available: URL. [Accessed: Sep. 3, 2026].

Jika jurnal meminta DOI, DOI sebaiknya dicantumkan jika tersedia.

14. Format Referensi Dataset

Karena penelitian Anda menggunakan dataset citra sampah, sumber dataset juga perlu dicantumkan apabila dataset berasal dari sumber publik.

Contoh pola:

[5] Author/Organization, "Dataset name," *Dataset Repository*, year. [Online]. Available: URL.

Kemudian di dalam artikel:

The waste image dataset was obtained from a publicly available dataset repository [5].

15. Format untuk DOI

Jika sebuah artikel memiliki DOI:

[6] A. Author, "Title of article," *Journal Name*, vol. 12, no. 3, pp. 100–110, 2024, doi: 10.xxxx/xxxxx.

DOI dapat dicantumkan pada akhir referensi. Pedoman IEEE menyatakan bahwa referensi yang memiliki DOI tetap diakhiri dengan tanda titik.

16. Penggunaan *et al.*

Jika terdapat banyak penulis, dapat digunakan et al. dalam kutipan teks.

Contoh:

Previous research demonstrated the effectiveness of deep learning for waste classification [7].

Atau jika nama penulis perlu disebut:

Smith et al. [7] proposed a deep learning model for waste classification.

Pedoman IEEE Reference Guide mengatur penggunaan *et al.* untuk sumber dengan banyak penulis dan memiliki ketentuan khusus terkait jumlah nama yang ditampilkan dalam daftar referensi.

17. Jangan Menggunakan "ibid." dan "op. cit."

Dalam daftar referensi IEEE, hindari:

ibid.

atau

op. cit.

Jika sumber yang sama dikutip kembali, gunakan nomor referensi yang sama.

Contoh:

CNN models can automatically learn hierarchical image features [3].

Kemudian beberapa paragraf berikutnya:

The learned features can subsequently be used for classification [3].

Bukan membuat nomor baru [9] untuk sumber yang sama.

IEEE secara eksplisit menyarankan agar *ibid.* dan *op. cit.* dihilangkan dari daftar referensi.

18. Jika Mengutip Bagian Tertentu dari Referensi

Jika Anda ingin menunjukkan halaman:

[3, pp. 20–25]

Jika mengacu pada gambar:

[3, Fig. 2]

Jika mengacu pada persamaan:

[3, eq. (5)]

Jika mengacu pada bagian tertentu:

[3, Sec. IV]

Format seperti ini juga dijelaskan dalam IEEE Reference Guide.

19. ATURAN PENTING UNTUK ARTIKEL ANDA

Untuk Development of a CNN-Based Household Waste Image Classification Model for Automatic Identification, saya sarankan menggunakan aturan berikut:

Bagian	Aturan
Gaya sitasi	IEEE
Kutipan dalam teks	[1], [2], [3]
Urutan nomor	Berdasarkan kemunculan pertama
Sumber yang sama	Menggunakan nomor yang sama
Nama penulis dalam teks	Tidak wajib
Tahun dalam teks	Tidak perlu
Dua sumber	[1], [2]
Banyak sumber	[1], [2], [3]
Daftar referensi	Bernomor
Nama penulis	Inisial + nama belakang
Judul artikel	Dalam tanda kutip
Nama jurnal	*Italic*
DOI	Dicantumkan jika tersedia
URL	Dicantumkan untuk sumber online jika diperlukan
ibid./op. cit.	Tidak digunakan

20. Contoh Sebelum dan Sesudah Diperbaiki

Format yang kurang sesuai IEEE

According to Simbolon et al. (2025), deep learning can be used to classify household waste. According to Luntungan et al. (2025), CNN can provide good classification results.

Format IEEE

Deep learning approaches have been applied to automatically classify household waste based on visual characteristics [1]. CNN-based approaches have also demonstrated their potential for automatic waste image classification [2].

Atau jika nama penulis memang penting:

Simbolon et al. [1] proposed a deep learning approach for household waste classification, while Luntungan et al. [2] investigated CNN-based classification methods.

21. HAL YANG SANGAT PENTING UNTUK SKRIPSI/JURNAL ANDA

Karena sebelumnya Anda melakukan revisi artikel dan diminta reviewer untuk menghilangkan nama penulis secara langsung dari paragraf sintesis literatur, pola yang paling aman untuk artikel Anda adalah:

Hindari:

According to Simbolon et al. (2025), ...

Gunakan:

Previous studies have demonstrated that deep learning can be applied to household waste classification [1].

Kemudian nomor [1] diarahkan ke referensi Simbolon et al. di bagian REFERENCES.

Dengan demikian, paragraf literatur Anda terlihat lebih akademis dan konsisten dengan gaya IEEE. IEEE juga menyarankan agar nama penulis tidak disertakan bersama nomor referensi kecuali nama tersebut memang diperlukan secara integral dalam kalimat.

VII. SIMPULAN

Berdasarkan penelitian mengenai pengembangan model klasifikasi citra sampah rumah tangga berbasis CNN untuk identifikasi otomatis, dapat disimpulkan bahwa model CNN dapat digunakan untuk mengklasifikasikan citra sampah rumah tangga ke dalam beberapa kategori, yaitu plastik, kertas, kaca, dan logam. Tahapan penelitian meliputi persiapan dataset, preprocessing citra, pelatihan model, evaluasi, serta penggunaan model terlatih untuk melakukan prediksi secara otomatis. Hasil evaluasi menunjukkan bahwa kinerja model dipengaruhi oleh jumlah dataset, konfigurasi pelatihan, dan metode evaluasi yang digunakan. Meskipun model CNN memperoleh akurasi yang tinggi pada pembagian data train-test split, hasil Stratified 5-Fold Cross-Validation menunjukkan performa yang lebih rendah. Hal ini menunjukkan bahwa akurasi tinggi pada pembagian data tunggal belum tentu menggambarkan kemampuan generalisasi model dengan baik, terutama karena jumlah dataset yang relatif kecil dan adanya kemungkinan overfitting. Berdasarkan perbandingan dengan metode transfer learning, EfficientNetB0 menunjukkan performa klasifikasi yang lebih baik dibandingkan CNN yang dikembangkan dari awal, MobileNetV2, dan ResNet50 pada dataset penelitian. Hal ini menunjukkan bahwa penggunaan model pretrained dapat memberikan keuntungan dalam melakukan ekstraksi fitur, terutama ketika dataset yang tersedia masih terbatas. Secara keseluruhan, penelitian ini menunjukkan bahwa deep learning dengan metode CNN memiliki potensi untuk digunakan dalam identifikasi otomatis jenis sampah rumah tangga. Namun, diperlukan pengembangan lebih lanjut berupa penambahan jumlah dan keragaman dataset, penggunaan citra sampah dalam kondisi lingkungan nyata, serta evaluasi yang lebih komprehensif untuk meningkatkan akurasi, ketahanan, dan kemampuan generalisasi model.

UCAPAN TERIMA KASIH

Dengan penuh rasa syukur, saya mengucapkan terima kasih kepada semua pihak yang telah menjadi bagian dari perjalanan panjang dalam menyelesaikan skripsi ini. Perjalanan ini bukan hanya tentang menyelesaikan sebuah penelitian, tetapi juga tentang belajar untuk bertahan, berproses, dan percaya bahwa setiap langkah kecil pada akhirnya akan membawa saya sampai pada titik ini. Terima kasih yang sebesar-besarnya saya sampaikan kepada Allah SWT, atas segala kekuatan, kesehatan, kesempatan, dan kemudahan yang diberikan hingga skripsi ini dapat diselesaikan.

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REFERENSI

[1] SIPSN, "Regulasi SIPSN," *Sipsn*, vol. 6, no. 2, pp. 162–171, 2025, [Online]. Available: https://r.search.yahoo.com/_ylt=AwrKFatTmzFoKwIA2K_LQwx.;_ylu=Y29sbwNzZzMEcG9zAzEEdnRpZAMEc2VjA3Ny/RV=2/RE=1749291092/RO=10/RU=https%3A%2F%2Fsipsn.menlhk.go.id%2Fsipsn%2F/RK=2/RS=iWggqPlPwaRitAMvE5H5Q58G.IA-

[2] Badan Pusat Statistik, "Metadata Statistik Kegiatan Sakernas," pp. 1–19, 2021, [Online]. Available: https://sirusa.web.bps.go.id/metadata/

[3] A. Ikhlas and B. Hendrik, "Literature Review: A Comparative Study of Waste Classification using Deep Learning Algorithms," *Sistemasi*, vol. 14, no. 3, p. 1360, 2025, doi: 10.32520/stmsi.v14i3.5163.

[4] C. J. Yi and C. F. Kim, "AI-Powered Waste Classification Using Convolutional Neural Networks (CNNs)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 15, no. 10, pp. 67–75, 2024, doi: 10.14569/IJACSA.2024.0151009.

[5] M. Diqi, "Waste Classification using CNN Algorithm," *Int. Conf. Inf. Sci. Technol. Innov.*, vol. 1, no. 1, pp. 130–135, 2022, doi: 10.35842/icostec.v1i1.17.

[6] G. Aprisia Bahagia and M. Akbar, "Klasifikasi Sampah Organik Dan Anorganik Menggunakan Metode Convolutional Neural Network (Cnn)," *JATI (Jurnal Mhs. Tek. Inform.*, vol. 8, no. 5, pp. 10349–10355, 2024, doi: 10.36040/jati.v8i5.11038.

[7] S. Agustiani, H. Haryani, A. Junaidi, R. R. Putri, and M. G. Adam Z, "Comparative Optimization of EfficientNetB3, MobileNetV2, and ResNet50 for Waste Classification," *J. Inform.*, vol. 12, no. 2, pp. 131–137, 2025, doi: 10.31294/inf.v12i2.27533.

[8] D. Sadida Aulia, H. Arwoko, and E. Asmawati, "Klasifikasi Sampah Rumah Tangga Menggunakan Metode Convolutional Neural Network," *Metik J.*, vol. 8, no. 2, pp. 114–120, 2024, doi: 10.47002/metik.v8i2.956.

[9] J. J. C. Simbolon, Robet, and Hendri, "Household Waste Image Classification Using Deep Learning Model," *J. Artif. Intell. Eng. Appl.*, vol. 5, no. 1, pp. 1681–1690, 2025, doi: 10.59934/jaiea.v5i1.1690.

[10] M. E. Purba, A. Z. Situmorang, G. L. Br Ginting, M. W. P. Lubis, and F. M. Sinaga, "Klasifikasi Sampah Organik dan Anorganik Menggunakan Algoritma CNN," *J. Sifo Mikroskil*, vol. 26, no. 1, pp. 37–54, 2025, doi: 10.55601/jsm.v26i1.1510.

[11] Luntungan Stephen Pieters, "Development of Automatic Waste Classification System using CNN-Based Deep Learning to Support Smart Waste Management," *INOVTEK Polbeng - Seri Inform.*, vol. 10, no. 1, pp. 214–224, 2025, doi: 10.35314/wst8mh87.

[12] J. Wang, "Application research of image classification algorithm based on deep learning in household garbage sorting," *Heliyon*, vol. 10, no. 9, p. e29966, 2024, doi: 10.1016/j.heliyon.2024.e29966.

[13] Visen and N. Charibaldi, "Penerapan Object Detection Menggunakan Deep Learning Yolov8 Untuk Mengidentifikasi Sampah Anorganik (Maksimal Sepuluh Objek) Dalam Satu Citra," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 12, no. 1, pp. 195–202, 2025, doi: 10.25126/jtiik.2025129012.

[14] M. F. Setiawan, A. H. Rismawyana, P. T. Informatika, C. Utara, and K. Cimahi, "Convolutional Neural Network (Cnn) Pada Klasifikasi Grade," vol. 13, no. 3, 2024.

[15] T. N. Sari, M. P. Sari, T. A. Putri, and R. Pashya, "Otomatisasi Klasifikasi Sampah Menggunakan Convolutional Neural Network (CNN) Sebagai Sistem Pendukung Keputusan," *Pros. SEMNAS INOTEK (Seminar Nas. Inov. Teknol.*, vol. 9, no. 1, pp. 720–729, 2025, [Online]. Available: https://proceeding.unpkediri.ac.id/index.php/inotek/article/view/7413/4935

[16] Y. Rayhan and A. P. Rifai, "Multi-class Waste Classification Using Convolutional Neural Network," *Appl. Environ. Res.*, vol. 46, no. 2, 2024, doi: 10.35762/AER.2024021.

[17] L. Rahmawati and S. Defianti, "Klasifikasi Jenis Sampah Menggunakan Convolutional Neural Network untuk Mendukung Pengelolaan Limbah Waste Type Classification Using Convolutional Neural Network for Supporting Waste Management," vol. 6, no. 1, pp. 61–68, 2026, doi: 10.59395/exaxyj37.

[18] Kartiko, A. Prima Yudha, N. Dimas Aryanto, and M. Arya Farabi, "Klasifikasi Sampah Menggunakan Convolutional Neural Network," *Indones. J. Data Sci.*, vol. 3, no. 2, pp. 72–81, 2022.

[19] M. Haqqi, L. Rochmah, A. D. Safitri, R. A. Pratama, and Tarwoto, "Implementation Of Machine Learning To Identify Types Of Waste Using CNN Algorithm," *J. Fasilkom*, vol. 14, no. 3, pp. 761–765, 2024, doi: 10.37859/jf.v14i3.8116.

[20] M. Chhabra, B. Sharan, M. Elbarachi, and M. Kumar, "Intelligent waste classification approach based on improved multi-layered convolutional neural network," *Multimed. Tools Appl.*, vol. 83, no. 36, pp. 84095–84120, 2024, doi: 10.1007/s11042-024-18939-w.

[21] A. Asmawati, Y. Kurniawan, and R. N. Fadilah, "EFISIENSI PEMILAHAN SAMPAH DAUR ULANG BERBASIS ANDROID MENGGUNAKAN MODEL CNN SSD-MOBILENET V2 Program Studi Sains

Data, Fakultas Sains dan Teknologi, Universitas Raharja," *Journal*, vol. 11, no. 2, pp. 2654–8704, 2025.

[22] A. Arishi, "Real-Time Household Waste Detection and Classification for Sustainable Recycling: A Deep Learning Approach," *Sustain.*, vol. 17, no. 5, 2025, doi: 10.3390/su17051902.

[23] A.-M. Al-Mamun, R. Hossain, M. M. M. Sharmin, E. Kabir, and M. A. Iqbal, "Garbage classification using convolutional neural networks (CNNs)," *Mater. Sci. Eng. Int. J.*, vol. 7, no. 3, pp. 140–144, 2023, doi: 10.15406/mseij.2023.07.00217.

Conflict of Interest Statement:
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