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Innovative CNN approach for reliable chicken meat classification in the poultry industry

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ABSTRACT

In response to the burgeoning need for advanced object recognition and classification, this research embarks on a journey harnessing the formidable capabilities of Convolutional Neural Networks (CNNs). The central aim of this study revolves around the precise identification and categorization of objects, with a specific focus on the critical task of distinguishing between fresh and spoiled chicken meat. This study's overarching objective is to craft a robust CNN-based classification model that excels in discriminating between objects. In the context of our research, we set out to create a model adept at distinguishing between fresh and rotten chicken meat. This endeavor holds immense potential in augmenting food safety and elevating quality control standards within the poultry industry. Our research methodology entails meticulous data collection, which includes acquiring high-resolution images of chicken meat. This meticulously curated dataset serves as the bedrock for both training and testing our CNN model. To optimize the model, we employ the 'adam' optimizer, while critical performance metrics, such as accuracy, precision, recall, and the F1-score, are methodically computed to evaluate the model's effectiveness. Our experimental findings unveil the remarkable success of our CNN model, with consistent accuracy, precision, and recall metrics all reaching an impressive pinnacle of 94%. These metrics underscore the model's excellence in the realm of object classification, with a particular emphasis on its proficiency in distinguishing between fresh and rotten chicken meat. In summation, our research concludes that the CNN model has exhibited exceptional prowess in the domains of object recognition and classification. The model's high accuracy signifies its precision in furnishing accurate predictions, while its elevated precision and recall values accentuate its effectiveness in differentiating between object classes. Consequently, the CNN model stands as a robust foundation for future strides in object classification technology. As we peer into the horizon of future research, myriad opportunities beckon. Our CNN model's applicability extends beyond chicken meat classification, inviting exploration across diverse domains. Furthermore, the model's refinement and adaptation for specific challenges represent an exciting avenue for future work, promising heightened performance across a broader spectrum of object recognition tasks.

1. Introduction

Chicken meat has long been recognized as a crucial protein source essential for human health [1]. In the realm of poultry consumption, ensuring the freshness and safety of chicken meat is of paramount importance. However, the escalating demand for this poultry product has brought about an alarming increase in negative incidents associated with it [2]. The widespread prevalence of fraudulent practices and the inherent difficulty in discerning between fresh and rotten chicken pose significant challenges for consumers and the poultry industry alike. Over the past few years, various regions have witnessed

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cases of unscrupulous vendors selling spoiled and, at times, even potentially hazardous chicken meat [3].

In light of these concerning developments, researchers have been diligently working on innovative solutions to address this issue. The identification of fresh, wholesome chicken meat versus its spoiled counterpart has taken center stage, primarily due to the pressing need to safeguard public health and consumer interests [4]. Spoiled chicken meat, which may contain harmful additives like formalin, can exhibit telltale signs such as aberrations in color, unpleasant odors, and noticeable physical alterations [5]. These distinguishing characteristics play a pivotal role in ensuring the safety of consumers and maintaining the integrity of the poultry industry.

Within this context, recent research has unveiled a groundbreaking approach to tackle the challenge of chicken meat quality classification. In a noteworthy study, the K-Nearest Neighbor (K-NN) method was employed to devise a comprehensive Chicken Meat Quality Classification System [6]. What makes this research particularly novel is the meticulous exploration of various K values, each representing a unique approach to classifying chicken meat quality. The results of this exhaustive investigation yielded a fascinating revelation: the accuracy levels fluctuated significantly across different K values. However, after rigorous calculations and exhaustive experimentation, it was conclusively established that the highest accuracy percentage, an impressive 80.95%, was achieved when K equaled 7. This critical finding has far-reaching implications for the implementation of the K-NN method in the poultry industry [7], [8].

This research represents a significant leap forward in addressing the pressing issue of identifying fresh and rotten chicken meat. By harnessing innovative technologies and conducting rigorous experimentation, it has not only shed light on the detection of spoiled chicken meat but has also provided a concrete and practical solution for the industry, ultimately safeguarding both public health and consumer confidence.

In the ever-evolving landscape of research, a series of studies have been dedicated to solving complex classification problems, shedding light on both the challenges faced and the cutting-edge solutions applied to various domains. A significant focus has been on the classification of chicken meat, where the identification of rotten and normal meat has been a pressing concern [9], [10]. The Learning Vector Quantization (LVQ) method was employed in one such study, revealing that the LVQ-based rotten chicken detection application accurately identified 22 out of 30 data samples, resulting in an overall accuracy rate of 73.33% [11]. While this showcases the potential of LVQ, it also underscores the intricate nature of the problem at hand.

In a separate investigation, the application of deep learning algorithms revolutionized the process of classifying images [12]. This study, employing image data as its dataset [13], delved into the application of deep learning techniques, particularly the Multilayer Perceptron (MLP). Drawing inspiration from the remarkable accuracy exhibited by deep learning algorithms in areas like hand gesture recognition [14]–[16], this research achieved an impressive accuracy rate of 99.61% in image classification [12]. These findings illuminate the transformative power of deep learning in image-based classification tasks.

Furthermore, in the realm of image classification, a distinct research venture utilized the Keras recognition method [17]–[19] to tackle the complex task of classifying Cendrawasih bird images [20]. The training process, which encompassed 10 epochs, led to accuracy and loss values of 0.00850 and 2.5658, respectively. This outcome serves as a testament to the efficacy of the Multilayer Perceptron (MLP) in effectively completing image classification tasks for unique subjects like the Cendrawasih birds [21], [22].

In this ever-evolving landscape, the Convolutional Neural Network (CNN) stands as a pinnacle of innovation [23]–[25]. Serving as an extension of the Multilayer Perceptron (MLP), CNNs are meticulously designed for processing two-dimensional data, such as images [26], [27] or even sounds [28]. The ability of CNNs to directly glean insights from images substantially reduces the programming complexity [29], further highlighting their significance in the domain of image classification.

These diverse research endeavors collectively underline the complexity and importance of classification challenges in various domains. They also emphasize how cutting-edge techniques, including deep learning, MLP, and CNN, have the potential to not only address these challenges but also open up new horizons in fields that rely heavily on data classification and analysis.

The overarching objective of this pioneering research initiative is to revolutionize the process of discerning between fresh and rotten chicken meat through the application of cutting-edge deep learning algorithms, specifically employing a Convolutional Neural Network (CNN) classification model. This innovative approach encompasses a comprehensive four-stage methodology, each playing a pivotal role in achieving precise and reliable meat classification results.

The initial stage involves the meticulous acquisition of high-quality images, laying the foundation for subsequent analysis. These images serve as the raw material upon which the deep learning model will be trained to make critical judgments about the meat's freshness. Following image acquisition, a critical step of pre-processing ensues, wherein the acquired images undergo meticulous refinement. This stage aims to enhance the quality and clarity of the images, allowing the CNN model to extract meaningful features effectively. The success of this stage is instrumental in ensuring the accuracy of the subsequent classification [30].

The heart of this research lies in the creation of a robust CNN model specifically tailored for the classification task at hand. This stage involves the development of a neural network architecture designed to learn intricate patterns and nuances within the chicken meat images, ultimately facilitating the accurate differentiation between fresh and rotten meat [31]. The culmination of these efforts leads to the final classification stage, wherein the trained CNN model is deployed to classify chicken meat with unprecedented precision. The anticipated outcome is a reliable method capable of distinguishing between fresh and spoiled chicken meat samples with a high degree of accuracy.

Beyond its technical prowess, this research endeavor holds significant promise for the broader community. It is expected that this method will serve as a valuable resource, not only for researchers and industry professionals but also for consumers. Providing a trustworthy means of discerning meat quality can empower individuals to make informed choices when purchasing chicken products, thereby contributing to food safety and consumer welfare.

Furthermore, the potential applications of this research extend into the burgeoning technology-driven chicken meat market industry. As a pioneering reference point, it has the potential to inspire further innovations and advancements in meat quality assessment technologies, ultimately benefiting both the industry and the general public. In summary, this research represents a groundbreaking stride in the realm of meat classification, leveraging deep learning algorithms to redefine how we identify fresh and rotten chicken meat. Its implications extend far beyond the laboratory, holding the potential to reshape consumer choices, enhance food safety, and drive technological progress within the chicken meat market industry.

2. Method

2.1. Dataset

The meticulous compilation of this dataset involved a hands-on approach, as objects were meticulously captured through the lens of a mobile phone equipped with an impressive 64-megapixel camera specification. These objects of interest were meticulously situated within the premises of a prominent Poultry Slaughtering House nestled in the bustling heart of Makassar City, located in the picturesque region of South Sulawesi.

This exceptional dataset comprises a substantial collection of 600 images, meticulously divided into two distinct classes, each boasting a significant trove of 300 images. Each image boasts impressive dimensions, measuring a generous 4000x3000 pixels. The high-resolution nature of these images serves as a testament to the dedication invested in ensuring that every intricate detail is faithfully captured.

In Fig. 1, you can visually explore a representative glimpse of this dataset, showcasing a curated selection of images drawn from the two distinct classes. These images not only serve as a visual preview of the dataset's richness but also underline the diversity and complexity of the objects meticulously documented during the photography process. This painstakingly curated dataset forms the foundation upon which this research builds its deep learning model for chicken meat classification.

Its exceptional image quality, rigorous categorization, and impressive volume reflect the commitment to precision that characterizes this research endeavor.

(a) (b)

Fig. 1. Fresh Chicken Meat (a) Rotten Chicken Meat (b)

Furthermore, to facilitate robust model training and evaluation, the dataset is thoughtfully partitioned into training and test image subsets. The training set comprises 480 image samples, equally distributed with 240 samples representing fresh chicken and 240 samples depicting rotten chicken. The test set, on the other hand, consists of 120 image samples, with 60 samples depicting rotten chicken. This meticulous partitioning ensures that the developed deep learning model is rigorously tested and validated against a diverse range of data, reflecting real-world conditions.

2.2. Convolutional Neural Network Models

Convolutional Neural Network (CNN) is one of the algorithms in Deep Learning. It is the result of the development of the Multi-Layer Perceptron (MLP) designed to process data in the form of a grid, including two-dimensional images such as images [32]. CNN is used for labeled data classification using the supervised learning method. Training data and target variables are required in the supervised learning method. Training data and target variables are required in supervised learning to group data into existing variables [33]. CNN is often used to identify objects or scenes, as well as to detect and segment objects. The CNN architecture consists of Feature Learning and Classification, as seen in Fig. 2.

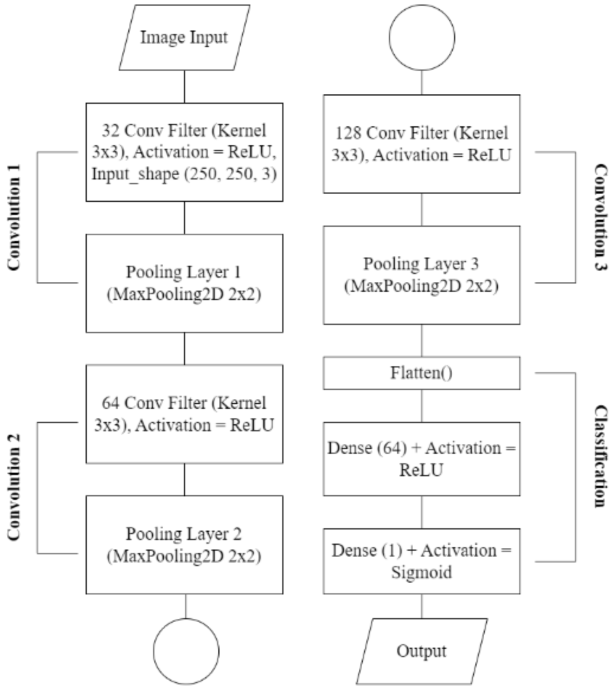

Fig. 2. CNN Architecture Design

This model utilizes Convolutional Neural Network (CNN) to process image data with dimensions of (250, 250, 3). There are three convolutional layers with 32, 64, and 128 filters each, and a ReLU activation function. After each convolutional layer, max pooling is applied with a size of (2, 2) to reduce the image dimensions. Next, the data is flattened into a one-dimensional vector and connected to a Dense layer with 64 neurons and ReLU activation. Finally, there is a last Dense Layer with 1 neuron and a sigmoid activation function for binary classification.

2.3. Compile Model

Additionally, as a pivotal step in the model development process, the model compile function meticulously configures the training process for our deep learning model. This pivotal configuration phase lays the foundation for robust and effective model training. In this setup, we employ the 'Adam' optimizer, a renowned algorithm celebrated for its proficiency in optimizing neural networks through adaptive learning rates. This choice underscores our commitment to efficient and effective training, harnessing the power of adaptive optimization to fine-tune model parameters. For the specific task of binary classification, where our objective is to distinguish between fresh and rotten chicken meat, we opt for the 'binary_crossentropy' loss function. This loss function is meticulously chosen for its suitability in tasks where the outcome falls into one of two categories, precisely mirroring our classification needs.

To gauge the model's performance and effectiveness during the training process, we specify 'accuracy' as the evaluation metric. This metric serves as a reliable yardstick, quantifying the model's ability to make accurate predictions and classify chicken meat correctly. Once this model compilation phase is executed, our deep learning model is primed and prepared for training with the meticulously collected and curated dataset. This strategic setup not only streamlines the training process but also sets the stage for our model to learn and adapt effectively, with the ultimate goal of achieving unparalleled accuracy in distinguishing between fresh and rotten chicken meat.

2.4. Calculation of Accuracy

Performance analysis often gravitates toward accuracy due to its inherent simplicity and interpretability, offering a clear gauge of a classification algorithm's adeptness at generating accurate predictions. This ratio, encapsulating correctly predicted instances within the total predictions, establishes a universal yardstick that facilitates comparative evaluations across diverse models and contexts. Particularly advantageous in datasets with a balanced distribution of classes, where parity between categories prevails, accuracy serves as an initial barometer to gauge a model's efficacy. However, its applicability becomes nuanced in scenarios featuring imbalanced datasets, where one class dominates the other. In such cases, a seemingly high accuracy might mask a model's failure to capture the minority class, as it gravitates toward predicting the majority. Moreover, when the costs associated with false positives and false negatives differ, accuracy might fail to reflect the real-world consequences of predictions. While accuracy provides a valuable entry point, delving into supplementary metrics like precision, recall, F1-score, or ROC curves fosters a more holistic comprehension of a model's performance, particularly in contexts where the objective surpasses mere overall correctness, necessitating a nuanced exploration of predictive capabilities. The equations used to calculate accuracy are shown in the following equations (1) [34].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\% \tag{1}$$

3. Results and Discussion

The commitment to attaining a very precise deep learning model is seen in the stringent training schedule utilized. The model underwent a rigorous training phase that lasted for 20 epochs, during which it utilized the 'Adam' optimizer. The rigorous training program was not wasted, as it produced exceptional outcomes. Fig. 3 displays the outcome of our efforts, which is an amazing accuracy score of 97.92%. The remarkable precision demonstrated by our model in differentiating between fresh and spoiled chicken flesh serves as a strong indication of its efficacy in improving food safety and quality control within the poultry sector.

The model's capacity to attain an exceptional accuracy rate in just 20 epochs demonstrates its strong architecture, effective optimization, and the highly qualified dataset it was trained on. The results inspire trust in the model's ability to produce accurate and dependable classifications, eventually benefiting both customers and the industry.

```
Epoch 6/20
12/12 [==============================] - 1s 66ms/step - loss: 0.0717 - accuracy: 0.9714 - val_loss: 0.2850 - val_accuracy: 0.9062
Epoch 7/20
12/12 [==============================] - 1s 73ms/step - loss: 0.0524 - accuracy: 0.9844 - val_loss: 0.1197 - val_accuracy: 0.9479
Epoch 8/20
12/12 [==============================] - 1s 73ms/step - loss: 0.0334 - accuracy: 0.9844 - val_loss: 0.0556 - val_accuracy: 0.9896
Epoch 9/20
12/12 [==============================] - 1s 67ms/step - loss: 0.0374 - accuracy: 0.9870 - val_loss: 0.0674 - val_accuracy: 0.9583
Epoch 10/20
12/12 [==============================] - 1s 68ms/step - loss: 0.0214 - accuracy: 0.9922 - val_loss: 0.1031 - val_accuracy: 0.9271
Epoch 11/20
12/12 [==============================] - 1s 71ms/step - loss: 0.0398 - accuracy: 0.9844 - val_loss: 0.0407 - val_accuracy: 0.9896
Epoch 12/20
12/12 [==============================] - 1s 70ms/step - loss: 0.1938 - accuracy: 0.9193 - val_loss: 0.3167 - val_accuracy: 0.8854
Epoch 13/20
12/12 [==============================] - 1s 77ms/step - loss: 0.1016 - accuracy: 0.9688 - val_loss: 0.1200 - val_accuracy: 0.9375
Epoch 14/20
12/12 [==============================] - 1s 77ms/step - loss: 0.0357 - accuracy: 0.9896 - val_loss: 0.2079 - val_accuracy: 0.9271
Epoch 15/20
12/12 [==============================] - 1s 71ms/step - loss: 0.0840 - accuracy: 0.9714 - val_loss: 0.3094 - val_accuracy: 0.9167
Epoch 16/20
12/12 [==============================] - 1s 65ms/step - loss: 0.0468 - accuracy: 0.9870 - val_loss: 0.1046 - val_accuracy: 0.9375
Epoch 17/20
12/12 [==============================] - 1s 65ms/step - loss: 0.0152 - accuracy: 0.9974 - val_loss: 0.1665 - val_accuracy: 0.9271
Epoch 18/20
12/12 [==============================] - 1s 65ms/step - loss: 0.0083 - accuracy: 0.9974 - val_loss: 0.1071 - val_accuracy: 0.9375
Epoch 19/20
12/12 [==============================] - 1s 66ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.0851 - val_accuracy: 0.9688
Epoch 20/20
12/12 [==============================] - 1s 64ms/step - loss: 0.0012 - accuracy: 1.0000 - val_loss: 0.0776 - val_accuracy: 0.9792
```

Fig. 3. Diagram of The Model Training Process

Fig. 2 clearly illustrates the useful insights obtained from the classification process utilizing the Convolutional Neural Network (CNN). This figure provides a detailed and visual depiction of the test findings, giving a complete picture of the system's performance. To thoroughly evaluate the system's efficiency, we utilized a widely recognized method in the field of categorization known as the confusion matrix. This matrix functions as a reliable tool for measuring several performance indicators, such as accuracy, precision, recall, and the F1-score.

The test results were used as the input dataset to create the confusion matrix in this assessment. The complex interaction of accurate positive predictions, accurate negative predictions, inaccurate positive predictions, and inaccurate negative predictions enabled the computation of these essential performance measures. The measurement chart, displayed in Fig. 4, provides a clear and succinct representation of the gathered results. This thorough evaluation is crucial in measuring the model's efficacy in differentiating between fresh and spoiled chicken flesh. It offers a detailed comprehension of the model's advantages and places that might be enhanced, eventually aiding in its advancement and its ability to enhance food quality and safety standards in the chicken business.

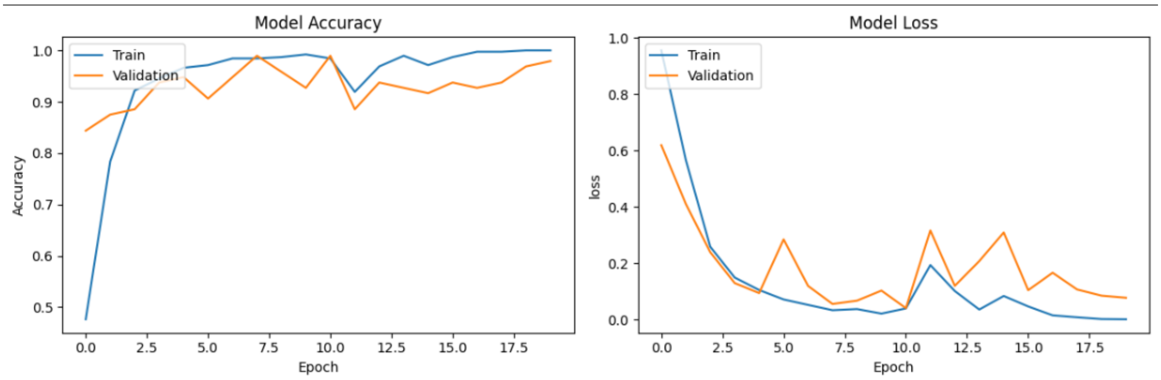

Fig. 4. The Chart Representing The Training Accuracy

The observations obtained from the confusion matrix provide a convincing representation of the model's ability to classify, showcasing a noteworthy degree of accuracy in differentiating between the two categories. More precisely, it emphasizes the accuracy with which the model classifies each data point. Upon closer analysis of the confusion matrix, it is evident that out of the 60 data points categorized as 'fresh', an impressive 58 have been accurately identified, highlighting the model's expertise in detecting fresh chicken flesh. Furthermore, inside the 'rotten' category, 53 data points have been correctly identified, which further strengthens the model's ability to effectively identify ruined meat.

Nevertheless, it is important to acknowledge that, similar to any categorization framework, there are instances where incorrect classifications may arise. Two data points belonging to the 'fresh' class and five data points belonging to the 'rotten' class have been mistakenly categorized. Although these misclassifications only make up a small portion of the dataset, they provide useful insights that may be used to improve and develop the model. Fig. 5 visually represents the classification outcomes, showing the properly categorized data points and the misclassified ones. This thorough assessment provides valuable insights for future iterations and enhancements, intending to enhance the accuracy and dependability of the model in differentiating between fresh and spoiled chicken flesh.

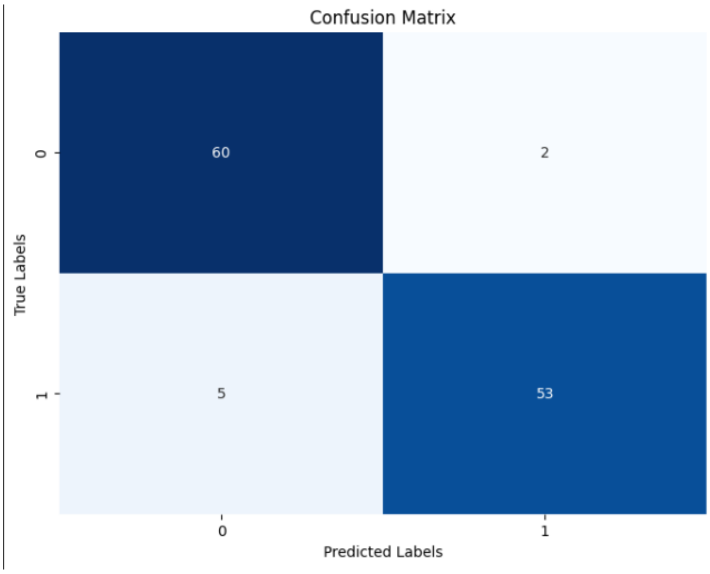

Fig. 5. Test Results Using Confusion Matrix

Certainly, the experimental data shown in Table 1 has undergone meticulous examination to produce crucial performance measures for the classification model. These measurements, including accuracy, precision, recall, and the F1-score, provide unique perspectives on the model's ability to classify data accurately. Accuracy offers a comprehensive assessment of the model's overall accuracy, indicating its performance across all categories. Precision refers to the model's accuracy in properly detecting positive occurrences, whereas recall measures its capability to catch all real positive cases. These two measures are especially useful for evaluating the impact of incorrect positive and negative classifications in the context of the classification problem.

The F1-score, which is calculated as the harmonic mean of accuracy and recall, offers a well-balanced evaluation of the model's performance. It is particularly valuable in situations where there is an unequal distribution of classes or where both precision and recall are equally important. The metrics obtained from the trial data provide a thorough assessment of the model's strengths and areas that need development. They serve as a vital tool for strengthening the model's capacity to reliably differentiate between fresh and rotting chicken flesh.

Table.1 Classification Performance Metrics for Fresh and Rotten Meat Chicken

	Accuracy	Precision	Recall	F1-Score	Support
Fresh Meat Chicken	0.94	0.92	0.97	0.94	62
Rotten Meat Chicken	0.94	0.96	0.91	0..94	58
Macro Average	0.94	0.94	0.94	0.94	120
Weighted Average	0.94	0.94	0.94	0.94	120

The comprehensive confusion matrix played a crucial role in enabling the analytical examination of the test data, which uncovered that the accuracy, recall, and F1-score values all reached an exceptional 94%. The classification model has demonstrated a high degree of accuracy, precision, and recall, as indicated by its convergence. The model's classification skills are demonstrated by the strong and constant values of these crucial metrics, indicating its robustness and reliability. A recall rate of 94% indicates that the model can effectively identify all true positive examples, while a precision rate of 94% demonstrates that the model is very accurate in correctly classifying positive occurrences. The model's competency may be further assessed using the harmonic F1-score, a balanced metric that combines precision and recall. These impressive measures not only confirm the model's capacity to accurately differentiate between fresh and spoiled chicken flesh, but they also demonstrate the model's potential to significantly enhance food safety and quality control in the poultry business.

4. Conclusion

In conclusion, the Convolutional Neural Network (CNN) classification model has demonstrated outstanding performance in object recognition and classification. With a remarkable 94% accuracy, precision, and recall, this model excels in effectively identifying and categorizing objects in the validation dataset. Its high accuracy signifies its ability to provide precise predictions, while the elevated precision and recall values underscore its proficiency in distinguishing between various object classes. As a result, the CNN model can be deemed a resounding success, laying a strong foundation for future advancements in object classification technology.

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