AMPLITUDO 4(1) (2025)

AMPLITUDO: Journal of Science & Technology Innovation

https://journals.balaipublikasi.id

Classification of Beef and Pork Using a Hybrid Model of ResNet-50 and Support Vector Machine (SVM)

Imam Syaukani[1], Siti Zarina Binti Mohd Muji[1], Chessda Uttraphan Eh Kan[1*]

[1] Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Parit Raja, Batu Pahat, Malaysia

Received: March 29, 2024
Revised: November 17, 2024
Accepted: February 24, 2025
Published: February 28, 2025

Corresponding Author:
Chessda Uttraphan Eh Kan
chessda@uthm.edu.my

DOI: 10.56566/amplitudo.v4i1.193

Abstract: Some people manipulate sales in marketplaces and other retail settings by combining beef and pork since the prices are so high. In addition to educating the public about these distinctions, this research aims to develop a technological solution for recognizing and differentiating between pork and beef. The proposed hybrid model, a combination of a Resnet-50 and a Support Vector Machine (SVM), is introduced for the classification of Beef and Pork Meat. In this hybrid model, the Resnet-50 functions as a powerful feature extractor, then utilizing its inherent ability to automatically capture distinctive features from diverse and highly specific meat image datasets. The SVM, serving as the binary classifier, effectively utilizes the extracted features for precise classification. The hybrid model achieves an outstanding accuracy of 100%, surpassing the performance of individual classifiers, with Resnet-50 achieving 97% accuracy and Resnet-50 achieving 97% obtained from the Hybrid model by gaining the best parameter C is 0,1 and the Kernel is linear. This remarkable outcome signifies the synergistic effectiveness of combining Resnet-50 and SVM.

Keywords: Beef; CNN; Pork; Resnet-50; Support Vector Machine

Introduction

Meat stands as a staple in human diets, offering a rich source of protein vital for cognitive and physical well-being. With its widespread consumption, the market is abundant with various meat types. Although categorized for sale, some traders capitalize on soaring beef prices, yielding significant profits with minimal investment. Amidst these practices, there is an unfortunate occurrence of meat adulteration (Lihayati et al., 2016). Consumer choices in meat purchases often hinge on factors such as safety, quality, and popularity, encompassing considerations like color, tenderness, flavor, and aroma (Farinda et al., 2018). Trust plays a pivotal role in shaping consumer preferences and behaviors, particularly when it comes to food choices and consumption habits (Nuhraini et al, 2018). Referencing Figure 3, the visual depiction highlights the contrasting textures between beef and pork (Fitrianto & Sartono, 2021; Lee et al., 2022.

The pervasive influence of technological progress on daily life significantly enhances individuals' efficiency in executing various tasks. Technology catalyzes more effective and time-efficient task completion (Kuhlman, 2009; Rustinsyah, 2019). A prime example of this impact is evident in the livestock and food sectors, where technology can aid the public in discerning between natural beef and pork meat (Li & Yang, 2023; Pauly et al., 2017). Given the challenge of distinguishing between the different textures of beef and pork, a digital approach is one of the alternatives to solve this problem (Neneng et al., 2016). One such technological solution involvesleveraging the power of Deep Learning, a rapidly advancing branch of Machine Learning (Junayed et al., 2019; Komuro et al., 2023; Tian et al., 2022), with Convolutional Neural Networks (CNN) at the forefront. Various architectural models, including LeNet, AlexNet, VGGNet, ResNet, EfficientNet, ResNet50, and DenseNet, exemplify the diversity within CNNs. Typically, these architectures consist of stacked convolutional layers, a pooling layer, and a fully connected layer. This technological integration holds promise for revolutionizing the identification and differentiation of meat types,

How to Cite:
Syaukani, I., Muji, S. Z. B. M., & Eh Kan, C. U. (2025). Classification of Beef and Pork Using a Hybrid Model of ResNet-50 and Support Vector Machine (SVM). *AMPLITUDO: Journal of Science and Technology Innovation*, 4(1), 65–70. https://doi.org/10.56566/amplitudo.v4i1.193

addressing the challenges posed by subtle textural variations (Navaneeth & Suchetha, 2019).

This study builds on the work of (Komuro et al., 2023), which successfully classified benign and malignant breast cancer histopathology imaging subtypes using a hybrid CNN- LSTM-based transfer learning approach. The dataset included 2480 clear images and 542 cancer images. The previous research achieved an outstanding 99% accuracy in the binary classification of benign and malignant cancer (Srikantamurthy et al., 2023). This success inspires our exploration of a similar hybrid model approach to differentiate between beef and pork meat in our current study.

This study aims to improve image quality, focusing on texture, marbling, color, and shape analysis using the CNN-ResNet50 method. By leveraging the CNN-ResNet50 architecture, which includes multiple convolutional layers (Akhtar et al., 2016; Attokaren et al., 2017), we intend to classify beef and pork meat effectively. To enhance the obtained results, we'll complement this architecture with an SVM (Support Vector Machine) (Datumaya Wahyudi Sumari et al., 2021; Utami Putri & Redi Susanto, 2020). In the contemporary technological landscape, deep learning has gained widespread popularity among engineers worldwide. This approach facilitates efficient data processing for engineers and employees. Therefore, this research will hybrid both models CNN-ResNet50 and SVM, aiming to enhance the accuracy and precision of the results (Agarap, 2017; Ahlawat & Choudhary, 2020; Eroğlu et al., 2021; Karthik & Muthupandi, 2023; Khairandish et al., 2022; Wulandari et al., 2020.).

Method

Figure 1 illustrates the comprehensive framework of the overall implementation. As depicted, the crucial stages involve the hybrid part. Once the data is trained, the subsequent step is image classification. This ensures that the constructed model attains accurate predictions for images of beef and pork meat, aligning with the objectives of this research.

The integration of a Convolutional Neural Network (CNN) with a Support Vector Machine (SVM) aims to enhance overall performance in a specific task or domain by leveraging the strengths of both techniques (Balarabe & Jordanov, 2021; İnik & Turan, 2018). The hybrid model aspires to create an optimal model by utilizing new feature extraction and SVMs' discriminative capacity, leading to improved accuracy, robustness, and interpretability. CNNs excel at extracting significant features from raw input data, particularly in tasks involving photos, videos, or sequential data. Their use of convolutional layers facilitates the development of hierarchical representations that capture meaningful patterns and structures. The hybrid model benefits from the CNNs' ability to extract rich and discriminative features.

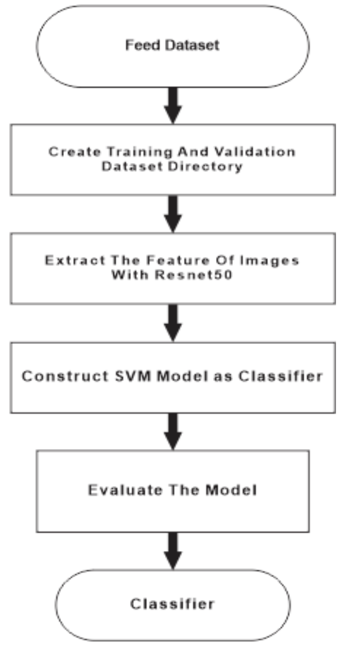

Figure 1. *Framework Diagram of Methodology.*

System Design

In this section on system design, various design aspects are emphasized to ensure the smooth training and validation of the system, covering all specified objectives. The system's model plays a crucial role in its functionality and data testing. The system comprises two models: CNN-ResNet50 and Support Vector Machine (SVM).

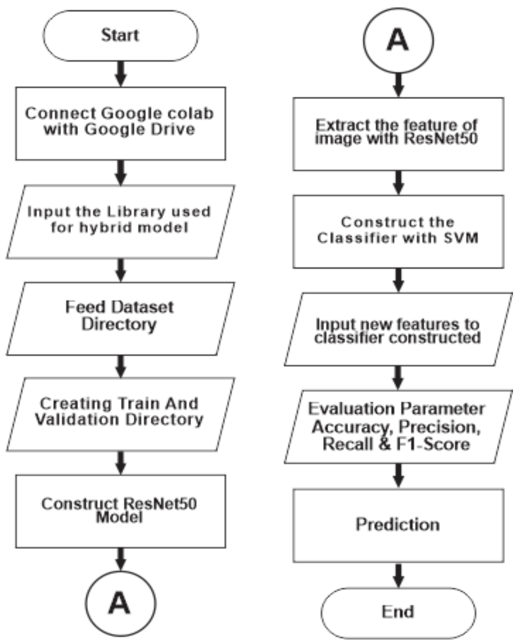

Figure 2. *Overall System Process.*

Figure 2 depicts the system setup process. Initially, the computer connects to Google Colab. The image location is linked to Google Drive before providing the data directory to Google Colab. Once the connection between Google Colab and Google Drive, where the images are stored, is established, the necessary libraries are imported, and access to the images is granted, ensuring there are no errors during the connection. Subsequently, feature extraction is performed using ResNet50, and the new features are used as input for the SVM classifier.

Subsequently, it is crucial to establish separate training and validation directories within Google Colab for the tested image data. This division ensures the proper organization of inputted images based on their assigned classes. During this process, the program determines the number of images present, encompassing both class-specific and total images used once the program is executed. Following this,the CNN and SVM models are constructed to validate the system's correctness. The next step involves inputting new features into the constructed models and fine-tuning the best parameters for image classification or prediction.

Result and Discussion

In the fine-tuning process, accuracy was commonly measured and evaluated after the best parameter tuned by the SVM classifier. Figure 5 displays the accuracy achieved after the training process was done by the grid-search CV. “Grid-search-best-params_” shows the best param for the classifier model. Next is declaring “y-pred” and calling the best estimator trained before, for predicting the images by the new features to be executed in the accuracy code. These results are valuable in making informed decisions, such as parameter adjustments, and modifications to the model architecture. Then the classifier model resulted in an accuracy of 100%.

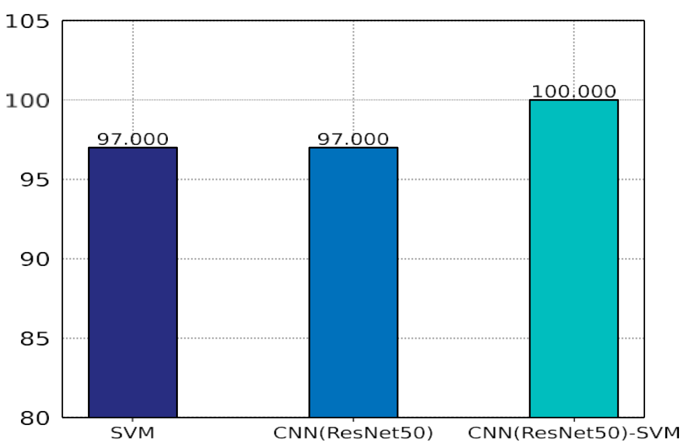

Figure 3. Comparing the Accuracy Single Model with Proposed Model.

Figure 3 depicts a graphic comparing SVM, CNN(ResNet50), and CNN(ResNet50)-SVM model. Therefore, these 3 models with the same number and type of datasets are tested to know the proposed performance. Table 1 illustrates the optimal parameters fine-tuned by the hybrid model. The parameter C is chosen to balance the margin and classification error, where a higher C value imposes a greater penalty for classification errors, and a lower C value implies a smaller penalty. In this instance, the best C value is determined as 0.1, indicating that the svc-classifier performs well for classification. When the data is not easily separable in a straight line, it becomes difficult for the SVM softmargin to find a clear division on the hyperplane. This results in lower accuracy andweaker generalization. To address this challenge, a kernel is used to project the data into a higher-dimensional space, allowing for more straightforward linear separation. Common kernel types include linear, polynomial, and radial basis function (RBF). In this study, the best-performing kernel is determined to be linear.

Classification Report

The classification report is a common evaluation metric used in machine learning and classification tasks. The classification report provides a details summary of the performance of a classification model by calculating various metrics for each class in the datasets. The commonly included metrics are precision, recall, F1 score, and support. Figure 4 shows the classification report generated for the hybrid CNN(ResNet50)-SVM model developed. The complete dataset comprises 210 images, with only 10 images allocated for testing in the test dataset. The accuracy score is 100%, with distinct classes for beef and pork. Otherwise, to know the performance is better than the single model, Figure 4.3 describes that the performance of the hybrid is better than SVM and CNN(ResNet50).

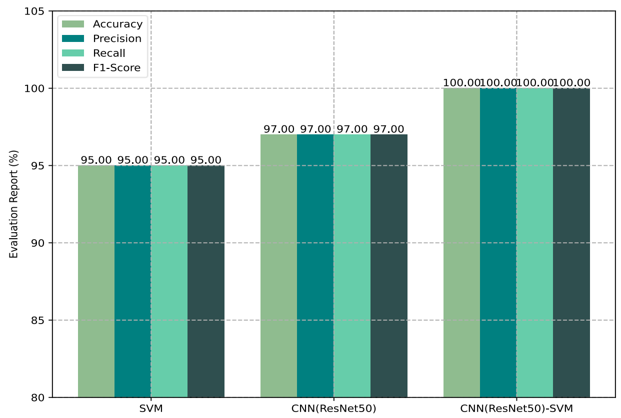

Figure 4. Evaluation Report of Single Model with Proposed Model.

```
[ ] grid_search.best_estimator_

[ ] grid_search.best_params_

    {'svc__C': 0.1, 'svc__kernel': 'linear'}

[ ] #predict using GridSearchcv best estimator

    y_pred = grid_search.best_estimator_.predict(X_val_features)

[ ] # Calculate accuracy
    accuracy = accuracy_score(y_val, y_pred)
    print("Accuracy:", accuracy)

    Accuracy: 1.0
```

Figure 5. Accuracy calculation

Confusion Matrix

Figures 6 and 7 showcase SVM and CNN (ResNet50), respectively, while Figure 8 illustrates the hybrid model CNN(ResNet50)-SVM for comparison. In Figure 8, the confusion matrix from the hybrid CNN(ResNet50)- SVM model is presented. Evaluating the confusion matrices from the three models tested, the hybrid model demonstrates superior performance compared to the other two individual models. In the SVM confusion matrix (Figure 8), there are 20 true positives (TP) and 19 true negatives (TN), with 0 false positives (FP) and 1 false negative (FN) indicating a lack of precision in predictions, with zero incorrect prediction out of 20 true positives and one incorrect prediction out of 19 true negatives. The CNN(ResNet50) confusion matrix (Figure 8) shows 20 TP and 19 TN, with 0 FP and 1 FN. While there are no false positive predictions, there's 1 false prediction out of 19 true negatives. On the other hand, the hybrid confusion matrix (Figure 7) performs well with 20 TP and 20 TN, and 0 FP and 0 FN. This suggests that the model built has no false predictions for either positive or negative outcomes.

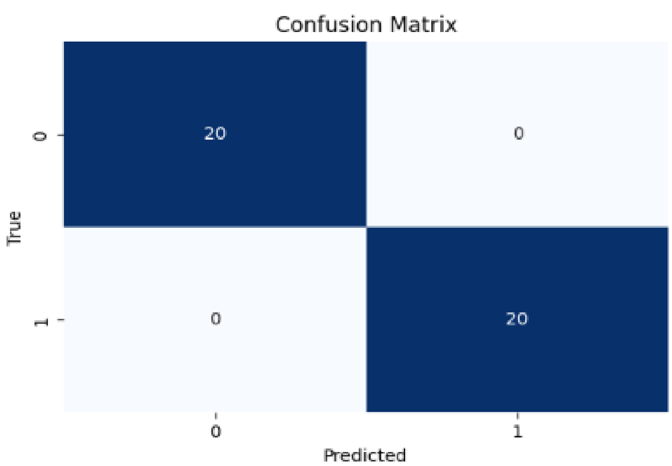

Figure 6. *SVM Confusion Matrix.*

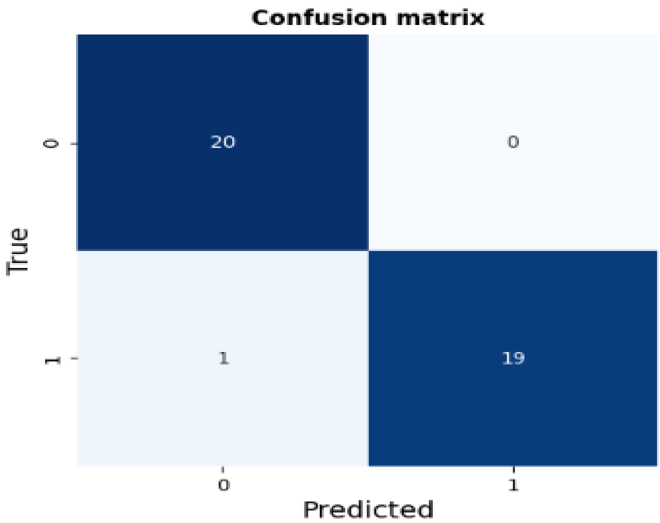

Figure 7. *CNN(ResNet50) Confusion.*

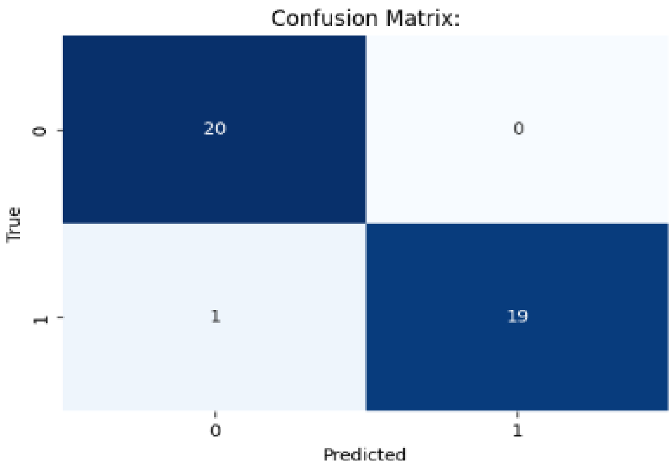

Figure 8. *CNN(ResNet50)-SVM Confusion Matrix.*

(a) (b)

Figure 9. *Texture difference,* (a) Beef (b) Pork.

Conclusion

The CNN(ResNet50)-SVM model demonstrated a remarkable ability, boasting an impressive accuracy rate of 100%. These outcomes underscored the CNN(ResNet50)-SVM model's robustness and efficacy, particularly in the realm of accurately identifying a diverse range of meat items. To further validate the proficiency of the CNN(ResNet50)-SVM model, an array of comprehensive assessments was executed. This included the generation of a confusion matrix and a detailed classification report, facilitated through the utilization of the Google Colab platform. These analytical tools served as a litmus test, providing valuable insights into the model's adeptness at correctly categorizing meat items, thus fortifying its reliability and real-world applicability. Contributions of this research to the realm of meat recognition by using technology. These findings illuminate the vast potential of improving to the application level as a precise and dependable tool for individuals. This technology holds the promise of significantly augmenting awareness of selecting of meat at any market, thereby contributing to improved belief of the customer to the trader and enhanced effectiveness in transactions at the market.

Acknowledgments
The authors would like to thank the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia for its support.

Author Contributions
All authors have read and agreed to the published version of the manuscript.

Funding
This research was funded by LPPNTB & Brida under West Nusa Tenggara Government.

Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of the paper.

References

Agarap, *A. F. (2017). An Architecture Combining Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for Image Classification*, Retrieved from http://arxiv.org/abs/1712.03541

Ahlawat, S., & Choudhary, A. (2020). Hybrid CNN-SVM Classifier for Handwritten Digit Recognition. *Procedia Computer Science*, 167, 2554–2560. https://doi.org/10.1016/j.procs.2020.03.309

Akhtar, S., Kumar, A., Ekbal, A., & Bhattacharyya, P. (2016). *A Hybrid Deep Learning Architecture for Sentiment Analysis.* https://www.domo.com/learn/data-never-sleeps-2

Asmara, R. A., Romario, R., Batubulan, K. S., Rohadi, E., Siradjuddin, I., Ronilaya, F., Ariyanto, R., Rahmad, C., & Rahutomo, F. (2018). Classification of pork and beef meat images using extraction of color and texture feature by Grey Level Co-Occurrence Matrix method. *IOP Conference Series: Materials Science and Engineering,* 434(1). https://doi.org/10.1088/1757899X/434/1/012072

Attokaren, D. J., Fernandes, I. G., Sriram, A., Murthy, Y. V. S., & Koolagudi, S. G. (2017). Food classification from images using convolutional neural networks. *IEEE Region 10 Annual International Conference, Proceedings/TENCON, 2017-Decem, 2801–2806.* https://doi.org/10.1109/Tencon.2017.8228338

Balarabe, A. T., & Jordanov, I. (2021). Lulc Image Classification With Convolutional Neural Network. *International Geoscience and Remote Sensing Symposium (IGARSS),* 3, 5985–5988. https://doi.org/10.1109/igarss47720.2021.9555015

Datumaya, W.S A., Alfian Bastami, A., & Rahmad, C., (2021). Pemilihan daging kelapa bermutu berdasarkan warna dan tekstur untuk produksi wingko berkualitas menggunakan metode support vector machine (SVM) dan fusi informasi. *Jurnal Teknologi Informasi Dan Ilmu Komputer*, *8*(3), 587-594. https://doi.org/10.25126/jtiik.2021834391

Eroğlu, Y., Yildirim, M., & Çinar, A. (2021). Convolutional Neural Networks based classification of breast ultrasonography images by hybrid method with respect to benign, malignant, and normal using mRMR. *Computers in Biology and Medicine*, 133. https://doi.org/10.1016/j.compbiomed.2021.104407

Farinda, R., Gede, I., Wijaya, P. S., Bimantoro, F., Firmansyah, Z., Sulton, C., & Wijaya, S. (2018). Beef Quality Classification based on Texture and Color Features using SVM Classifier Pembuatan Aplikasi Catalog 3D Desain Rumah Sebagai Sarana Promosi Dengan Menggunakan Unity 3D View project Pornographic Image Recognition View project Beef Quality Classification based on Texture and Color Features using SVM Classifier. *Journal of Telematics and Informatics,* 6(3), 201–213. https://doi.org/10.12928/jti.v6i3

Fitrianto, A., & Sartono, B. (2021). Image Classification of Beef and Pork Using Convolutional Neural Network in Keras Framework. International journal of science, engineering, and information technology. 5(2). https://doi.org/10.21107/ijseit.v5i02.9864

İnik, Ö., & Turan, B. (2018). Classification of Animals with Different Deep Learning Models. *Journal of New Results in Science,* 7(1), 9-16. Retrieved from https://dergipark.org.tr/en/pub/jnrs/issue/36616/387258#article_cite

Junayed, M. S., Jeny, A. A., Atik, S. T., Neehal, N., Karim, A., Azam, S., & Shanmugam, B. (2019). AcneNet - A deep CNN based classification approach for acne classes. Proceedings of 2019 *International Conference on Information and Communication Technology and Systems, ICTS 2019, 203–208.* https://doi.org/10.1109/ICTS.2019.8850935

Karthik, B. U., & Muthupandi, G. (2023). SVM and CNN based skin tumor classification using WLS smoothing filter. *Optik*, 272. https://doi.org/10.1016/j.ijleo.2022.170337

Khairandish, M. O., Sharma, M., Jain, V., Chatterjee, J. M., & Jhanjhi, N. Z. (2022). A Hybrid CNN-SVM Threshold Segmentation Approach for Tumor Detection and Classification of MRI Brain Images. *IRBM*, 43(4), 290–299. https://doi.org/10.1016/j.irbm.2021.06.003

Komuro, J., Kusumoto, D., Hashimoto, H., & Yuasa, S. (2023). Machine learning in cardiology: Clinical application and basic research. In *Journal of Cardiology*. Japanese *College* of Cardiology (Nippon-Sinzobyo-Gakkai) https://doi.org/10.1016/j.jjcc.2023.04.020

Komuro, J., Kusumoto, D., Hashimoto, H., & Yuasa, S. (2023). Machine learning in cardiology: Clinical application and basic research. In *Journal of Cardiology. Japanese College of Cardiology (Nippon-Sinzobyo-Gakkai).* https://doi.org/10.1016/j.jjcc.2023.04.020

Kuhlman, D. (2009). A Python Book: Beginning Python, Advanced Python, and Python Exercises.

Lee, J. M., Jung, I. H., & Hwang, K. (2022). Classification of Beef by Using Artificial Intelligence. *Webology*, 19(1), 4639–4647. https://doi.org/10.14704/web/v19i1/web19308

Li, Q., & Yang, W. (2023). An effective vehicle road scene recognition based on improved deep learning. *Measurement: Sensors*, 30, 100916. https://doi.org/10.1016/j.measen.2023.100916

Lihayati, N., Pawening, R. E., Furqan, M., Informatika, J. T., Jadid, N., & Probolinggo, P. (2016). Klasifikasi Jenis Daging Berdasarkan Tekstur Menggunakan Metode Gray Level Coocurent Matrix. *Prosiding SENTIA 2016-Politeknik Negeri Malang. Retrieved from https://risbang.unuja.ac.id/media/arsip/upload_file_sertifikat_dan_surat_tugas/2016_Furqon_Jenis_Dagang.pdf*

Navaneeth, B., & Suchetha, M. (2019). PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications. *Computers in Biology and Medicine,* 108, 85–92. https://doi.org/10.1016/j.compbiomed.2019.03.017

Neneng, N., Adi, K., & Isnanto, R. (2016). Support Vector Machine Untuk Klasifikasi Citra Jenis Daging Berdasarkan Tekstur Menggunakan Ekstraksi Ciri Gray Level Co-Occurrence Matrices (GLCM). *Jurnal Sistem Informasi Bisnis,* 6(1), 1. https://doi.org/10.21456/vol6iss1pp1-10

Nuhraini, F., & Reza Ferasyi, T. (2018). Study of Beef Consumer Consideration Based On the Concept of Halal and Economic Factors in Butchery of Lambaro, Aceh Besar. *Jurnal Medika Veterinaria.* 12(1), 62–69. https://doi.org/10.21157/j.med.vet.v1

Pauly, L., Peel, H., Luo, S., Hogg, D., & Fuentes, R. (2017). Deeper Networks for Pavement Crack Detection. *34th International Symposium in Automation and Robotics in Construction.* https://doi.org/10.22260/ISARC2017/0066

Rustinsyah, R. (2019). The significance of social relations in rural development: A case study of a beef-cattle farmer group in Indonesia. *Journal of Co-Operative Organization and Management, 7(2).* https://doi.org/10.1016/j.jcom.2019.100088

Srikantamurthy, M. M., Rallabandi, V. P. S., Dudekula, D. B., Natarajan, S., & Park, J. (2023). Classification of benign and malignant subtypes of breast cancer histopathology imaging using hybrid CNN-LSTM based transfer learning. *BMC Medical Imaging*, 23(1). https://doi.org/10.1186/s12880-023-00964-0

Tian, Y., Su, D., Lauria, S., & Liu, X. (2022). Recent advances on loss functions in deep learning for computer vision. In *Neurocomputing* (Vol. 497, pp. 129–158). Elsevier B.V. https://doi.org/10.1016/j.neucom.2022.04.127

Utami Putri, N., & Redi Susanto, E. (2020). Klasifikasi Jenis Kayu Menggunakan Support Vector Machine Berdasarkan Ciri Tekstur Local Binary Pattern. *CYBERNETICS*, 4(02), 93–100. http://dx.doi.org/10.29406/cbn.v4i02.2324

Wulandari, I., Yasin, H., & Widiharih, T. *(2020). Klasifikasi Citra Digital Bumbu Dan Rempah Dengan Algoritma Convolutional Neural Network (CNN).* https://ejournal3.undip.ac.id/index.php/gaussi/