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COMPARISON OF CNN AND SVM ALGORITHMS FOR BONE CANCER DISEASE CLASSIFICATION BASED ON IMAGE DATA

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Abstract

This research is motivated by the high urgency of early diagnosis in bone cancer cases to reduce patient mortality rates. This study comparatively analyzes the performance of the Convolutional Neural Network (CNN) algorithm with ResNet50 architecture, Support Vector Machine (SVM), and their integration in a Hybrid CNN-SVM model for medical image classification. The research methodology involved a dataset of 8,814 radiological images processed through normalization and augmentation stages. In single-model testing, the end-to-end ResNet50 architecture achieved an accuracy of 87%, but showed limitations in generalizing microscopic textures at the softmax classification layer. On the other hand, the SVM algorithm supported by manual Histogram of Oriented Gradients (HOG) feature extraction demonstrated significant stability with an accuracy of 93.58%, proving the superiority of the optimal margin method in handling specific feature dimensions in medical images. The crucial finding in this study shows that the Hybrid CNN-SVM model—which utilizes ResNet50 as an automatic feature extractor and SVM as the final classifier—achieved peak performance with an accuracy of 95.18%, Precision value of 0.98, Recall of 0.96, and AUC of 0.98. These results confirm that the synergy between CNN hierarchical feature extraction and SVM classification robustness can significantly minimize the risk of false negatives, making it highly recommended as a reliable Computer-Aided Diagnosis (CAD) instrument to assist medical practitioners in early detection of bone cancer.

Keywords: *CNN, SVM, Hybrid CNN-SVM, Bone Cancer, ResNet50, Medical Image Classification.*

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1. INTRODUCTION

Awareness of the importance of health as a fundamental aspect of life encourages people to adopt healthy lifestyles. Preventive efforts can be implemented through regular physical activity and balanced nutritional intake, particularly calcium-rich foods. However, the complexity of clinical manifestations and disease etiology continues to escalate, significantly affecting community health patterns. In reality, the dynamics of disease mutation and development are often one step ahead of the capabilities and therapeutic interventions developed by experts [1].

The modern shift toward unhealthy lifestyles in contemporary society has triggered an increase in the prevalence of various pathologies, ranging from mild to chronic clinical manifestations. One disease with high morbidity that has become a global health challenge in recent decades is cancer. This malignancy risk escalation correlates linearly with demographic factors, such as population growth, high parity rates in reproductive age groups, and an increasing proportion of the elderly population. According to the WHO 2008 report, cancer ranks second as the etiology of global mortality after cardiovascular disease, with an estimated mortality of 7.6 million people or equivalent to 21% of the total burden of non-communicable diseases worldwide [2].

Osteosarcoma is one type of primary bone malignancy with high prevalence in children and adolescents. The early clinical manifestations of this disease are generally characterized by bone pain that worsens at night or during physical activity. Alongside osteosarcoma, Ewing's sarcoma is another bone malignancy frequently diagnosed in childhood, often accompanied by more evident systemic symptoms including fever, significant weight loss, and chronic fatigue [3]. According to the Indonesian Ministry of Health (2023), although bone cancer is a rare type of cancer, its impact is very significant, especially in young age groups, such as cases of osteosarcoma and chondrosarcoma [4].

Artificial Intelligence (AI) is a branch of scientific study that continues to experience rapid development. One of its fundamental branches is computer vision, a discipline focused on computational methodologies enabling computers to identify and analyze observed objects. In the biomedical sector, the combination of AI and machine learning innovations opens new paradigms, particularly for facilitating early detection and pathology classification through automatic and precise medical image analysis [5].

In the domain of pattern recognition, machine learning algorithms including SVM and CNN have been widely implemented to solve classification tasks, including in medical imaging. Both architectures have comparative advantages in exploring high-dimensional data. In addition, both SVM and CNN have proven effective in identifying and extracting complex and latent features that are visually difficult for humans to analyze manually [6]. SVM has become a widely used machine learning method because it can effectively form decision boundaries between data groups [7]. CNN is one of the most advanced deep learning architectures in the image processing domain. Various studies have proven that CNN has high effectiveness and accuracy in recognizing various types of diseases based on medical images, although its computational performance is highly influenced by dataset characteristics, model architecture complexity, and the specific application objectives being developed [8].

Several previous studies have provided relevant insights. Gina and Ninuk found that CNN achieved 96% accuracy while SVM obtained 94% in skin disease classification, indicating CNN superiority for high-precision systems [9]. Research by Abdul et al. showed CNN achieved 99.7% accuracy in brain tumor classification, outperforming ANN and SVM [10]. A Systematic Literature Review by Qurrata and Billy confirmed CNN as the highest-performing method with over 90% accuracy in palm oil disease classification, surpassing KNN and SVM [11]. Prayesy found CNN achieved 92% accuracy while SVM recorded the lowest at 78% due to limitations with high-dimensional data [6]. In contrast, I Putu Agus et al. found SVM more effective than CNN (61.39% vs 32-35%) in facial expression recognition [12].

Based on these conditions, this research is directed to examine the comparison of the capabilities of CNN and SVM algorithms in the context of bone cancer disease classification based on image data, and further explore the potential of Hybrid CNN-SVM integration as an optimal classification instrument.

2. RESEARCH METHOD

This study is categorized as comparative quantitative research that analyzes and compares the performance of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) algorithms in detecting bone cancer disease using image data. The research was conducted over approximately eight months from September 2024 to April 2025.

2.1 Dataset

The dataset used consists of bone cancer radiological images obtained from the Kaggle platform (https://www.kaggle.com/datasets/bhaumik12/bone-cancer-detection). The dataset contains a total of 8,814 images with two classification classes: Cancer and Normal. The dataset was divided into three subsets: 70% for training (~6,170 images), 15% for validation (~883 images), and 15% for testing (~872 images), as shown in Figure 1.

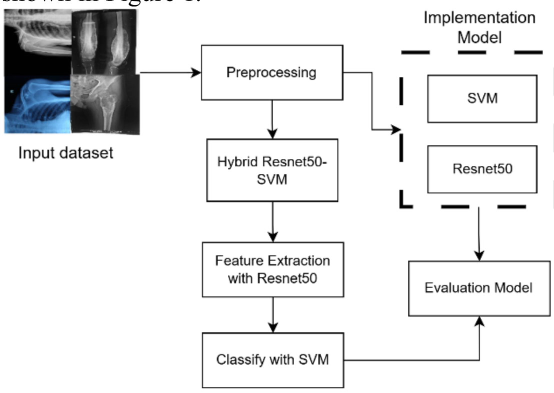


Figure 1. Research Work Procedure

2.2 Data Processing

Data preprocessing was performed to organize, modify, and clean the data to improve quality. All images were resized to 256×256 pixels before being fed into the model. Image augmentation techniques were applied to combat overfitting and improve model performance, including: random rotation (rotation_range), horizontal and vertical shifting (width_shift_range, height_shift_range), geometric shearing (shear_range), random scaling (zoom_range), and horizontal/vertical flipping (horizontal_flip, vertical_flip). Additionally, pixel values were normalized to the range [0, 1] before model input.

2.3 Modelling CNN (ResNet50)

Convolutional Neural Network (CNN) is a deep learning method specifically developed for processing grid-pattern data such as images. The ResNet50 architecture, developed by Microsoft Research in 2015, consists of 50 layers (48 convolutional layers, one MaxPool layer, and one average pool layer). It is one of the most important innovations in computer vision that allows training of deeper networks without encountering the vanishing gradient problem through its residual connections. In this research, ResNet50 was applied end-to-end as a complete classification pipeline using a softmax output layer [14]. In this research, the applied testing parameters consist of several epochs. Each epoch is initialized and its performance is then compared.

2.4 Modelling SVM

Support Vector Machine (SVM) is a machine learning method that identifies the optimal hyperplane as a decision boundary to separate classes in feature space based on margin maximization. When faced with nonlinearly separable data characteristics, this algorithm applies the kernel trick, projecting data toward a higher-dimensional space so that its distribution patterns can be differentiated linearly. In this research, SVM was implemented using manual feature extraction through the Histogram of Oriented Gradients (HOG) method to capture edge structure and geometric shapes in radiological bone images before classification [13][15].

2.5 Hybrid CNN-SVM Model

The Hybrid approach combines the strengths of both algorithms: the ResNet50 architecture is used as an automatic Feature Extractor by removing the last Fully Connected layer, and the features extracted by CNN are then fed into the SVM which acts as the final classifier. This integration leverages the hierarchical feature extraction capability of CNN's deep architecture with the optimal margin classification robustness of SVM, aiming to overcome the generalization limitations of either method when used individually.

2.6 Evaluation Metrics

Model performance was evaluated using four fundamental metrics derived from the Confusion Matrix:

Accuracy: (TP + TN) / (TP + TN + FP + FN) — represents the overall correct prediction rate across all classes.

Precision: TP / (TP + FP) — measures the quality of positive predictions, indicating how many predicted cancer images are actually cancer.

Recall (Sensitivity): TP / (TP + FN) — the most critical metric in the medical domain, measuring the system's ability to retrieve all actual cancer cases without missing any.

F1-Score: 2 × (Precision × Recall) / (Precision + Recall) — the harmonic mean that balances precision and recall values, especially useful when there is class imbalance.

3. RESULT AND DISCUSSION

This section presents the experimental findings from bone cancer image classification using a total of 8,814 data items. The experiment compares three model scenarios to determine the best performance in detecting pathological patterns in medical radiological images.

3.1 CNN (ResNet50) Training Analysis

The implementation of the CNN model using the ResNet50 architecture was carried out to thoroughly test the feature extraction and classification capabilities of bone cancer images. Parameter determination in the test was carried out with several parameters, such as the initialization of the number of epochs, learning rate and batch size. The best performance is achieved when the number of epochs is initialized to 50, the learning rate is 0.001, and the batch size is 32.

Based on the test results, the pure CNN model achieved 87% accuracy from a total of 872 test data. As visualized in Figure 2, although the model shows positive learning progress on the training curve with a continuously decreasing loss value, this indicates that the training process is not yet stable, because from several determinations of the number of epochs, the higher the number of epochs initialized, the better the model improvement, although it requires a very long time in the training process.

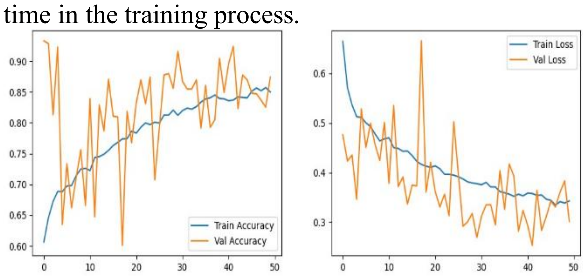
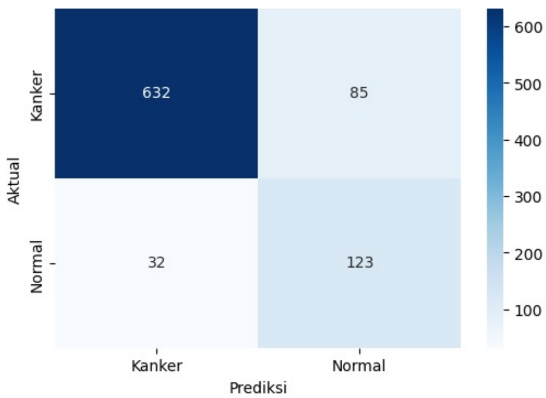


Figure 2. Accuracy and Loss Training Graph of ResNet50 Architecture

A more in-depth analysis using the confusion matrix in Figure 3 reveals that of the 717 actual Cancer class data, 85 were incorrectly classified as Normal. Meanwhile, in the Normal class, only 123 of the 155 data were correctly classified, meaning that 32 data were classified as Cancer. This classification error resulted in a low precision value for the Normal class, which was only 0.59, a recall of 0.79, and an F1 score of 0.68. For the Cancer class, the precision value was 0.95, a recall of 0.88, and an F1 score of 0.92. The cause of the still high bias is the unbalanced number of classes. As a result, many data are still incorrectly classified.



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============================================================
              precision    recall  f1-score   support

      Kanker       0.95      0.88      0.92       717
      Normal       0.59      0.79      0.68       155

    accuracy                           0.87       872
   macro avg       0.77      0.84      0.80       872
weighted avg       0.89      0.87      0.87       872
```

Figure 3. CNN Confusion Matrix and Classification Report

3.2 SVM (Manual Feature) Performance Analysis

The second experiment used the SVM algorithm with manual feature extraction using the Histogram of Oriented Gradients (HOG). Unlike CNN, SVM demonstrated significant robustness in processing grayscale feature characteristics in bone images. Test results showed highly consistent accuracy at 95.48% on training, 94.33% on validation, and 93.58% on testing. The pie chart in Figure 4 confirms the model's sensitivity with a prediction proportion of 86.6% for the Cancer class, proving that the SVM algorithm is very effective in optimizing class separation through the appropriate kernel function.

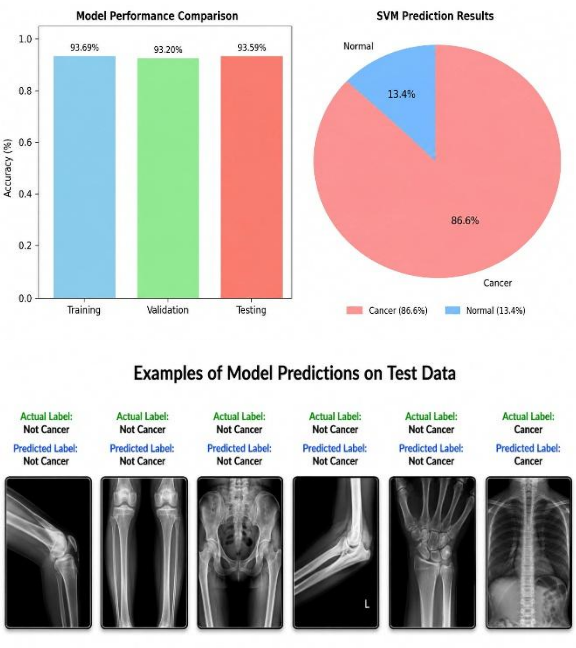

Figure 4. SVM Model Accuracy Comparison and Prediction Proportion

3.3 Hybrid CNN-SVM Performance Analysis

In accordance with the research objective to optimize classification, the Hybrid method was tested by combining the strengths of both algorithms. The results of the CNN-SVM Hybrid model test showed a significant increase in the model's performance in classifying bone cancer. The accuracy obtained with the CNN-SVM hybrid method was 0.95, the Precision value for the cancer class was 0.98, and the Recall was 0.94. Meanwhile, for the normal class, the precision obtained was 0.76 and the recall was 0.90. The robustness of this model is clearly visible in Figures 5 and 6.

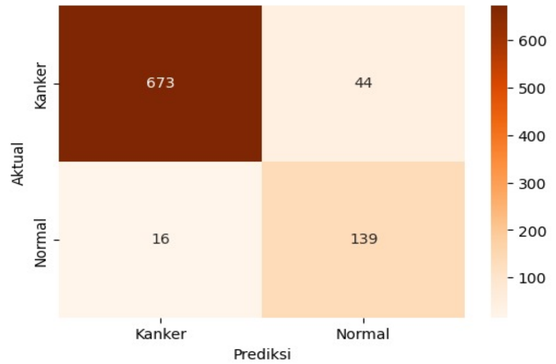

Figure 5. Confusion Matrix of Optimized Hybrid CNN-SVM Method

The Confusion Matrix shows that the model successfully classified 691 Cancer data accurately from the total test data, minimizing classification errors in both classes significantly. The ROC curve in Figure 6 with an AUC value of 0.98 confirms that this integration provides near-perfect performance in distinguishing between normal and pathological bone images, surpassing the use of pure CNN on this dataset. This approach proved capable of covering the weaknesses of pure CNN, while leveraging the deep feature extraction capabilities of the ResNet50 architecture.

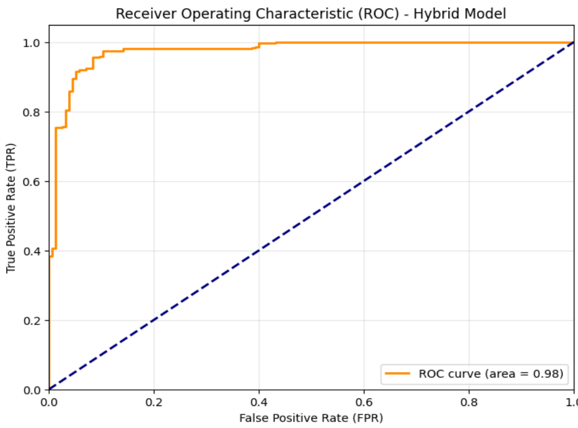

Figure 6. ROC Curve of Hybrid CNN-SVM Model with AUC Value 0.98

4. DISCUSSION

The initial stage that determines the success of this classification is the effectiveness of image feature extraction. In the pure SVM method, the use of HOG has proven capable of capturing edge structures and geometric shapes in radiological bone images stably, as reflected in the accuracy consistency in Figure 4. However, the main advantage in this research lies in the use of ResNet50 as an automatic feature extractor in the Hybrid model. The deep CNN architecture allows the system to capture microscopic features and complex textures that may not be captured by manual feature extraction, which then becomes high-quality raw material for the SVM classifier to determine class boundaries.

The combination of CNN feature extraction advantages with the optimal margin classification robustness of SVM produces a significant performance improvement. The Hybrid CNN-SVM model achieves 95.18% accuracy compared to 76% for pure CNN and 93.58% for pure SVM. The AUC of 0.98 further validates the near-perfect class separation capability of the hybrid approach.

From a clinical perspective, the achievement of a Recall value of 0.96 in the Hybrid model means the system has a very low failure rate in detecting disease presence, minimizing the risk of False Negative outcomes—patients with cancer being diagnosed as normal. With stable test accuracy at 95%, this model offers great potential to be applied as a Computer-Aided Diagnosis (CAD) system that can help medical practitioners perform early screening more quickly and accurately.

Table 1. Performance Comparison of Three Models

Model	Accuracy	Precision	Recall	AUC
CNN (ResNet50)	87%	0.77	0.84	-
SVM (HOG)	93.58%	-	86.6%	-
Hybrid CNN-SVM	**95.18%**	**0.98**	**0.96**	**0.98**

5. CONCLUSION

Based on the series of research stages covering data acquisition, image preprocessing, feature extraction, and final evaluation of bone cancer disease classification, it can be concluded that the integration of artificial intelligence technology has great potential in assisting the medical diagnosis process. Empirical test results show that the single CNN model with ResNet50 architecture provides baseline performance with an accuracy of 87%, showing limitations in capturing fine bone texture nuances in radiological images, resulting in notable false negative rates.

The SVM algorithm combined with manual HOG feature extraction demonstrated far more stable and competitive performance compared to single CNN, with an accuracy of 93.58%. The advantage of SVM lies in its ability to define an optimal separating hyperplane between data classes, which proves very effective on medical datasets with specific feature dimensions.

The main conclusion of this research establishes that the Hybrid CNN-SVM method is the most superior approach with the highest accuracy of 95.18% and an AUC value of 0.98. This success is driven by the synergy between ResNet50's automatic hierarchical feature extraction capability and SVM's robustness as the final classifier. This integration significantly minimizes the interpretation errors experienced by single models, producing a classification system that is not only mathematically accurate, but also has high reliability to be considered as a decision-support instrument for professional medical personnel in early bone cancer detection.

For future development, it is recommended to explore modern CNN architectures such as DenseNet, EfficientNet, and Vision Transformer (ViT), strengthen model generalization through multi-center datasets from various radiology laboratories, and develop an integrative web or mobile-based software application adaptive to medical workflows.

6. REFERENCES

[1] K. Sukmawati dan A. Pujiyanta., 'Deteksi Penyakit Tulang Menggunakan Jaringan Saraf Tiruan Dengan Metode Backpropagation,' *Jurnal Ilmiah Teknik Informatika*, Vol 2 (2). Pp.233-246. 2014.

[2] Ranti Restuti, 'Epidemiologi Kanker di Indonesia,' Jurnal Kesehatan Masyarakat, 2020.

[3] D. W. P. J. Kaunang, 'BIOMEDIK III: Patologi Tumor Tulang,' Universitas Sam Ratulangi, 2021.

[4] R. D. Destianti et al., 'Model Klasifikasi Tingkat Keparahan Tumor Tulang Menggunakan Algoritma Decision Tree Berbasis Fitur Klinis,' *JOURNAL OF COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE (JCSAI),* Vol 2 (3) 2025. [Online]. Available: https://ruangjurnal.or.id

[5] M. R. Efrian et al., 'Image Recognition Berbasis CNN untuk Mendeteksi Penyakit Kulit pada Manusia,' *Jurnal POLEKTRO*, vol. 11, no. 1, 2022.

[6] P. A. Prayesy, 'Studi Perbandingan Metode SVM, Random Forest, dan CNN untuk Klasifikasi Penyakit Kulit,' *Jurnal Kecerdasan Buatan dan Teknologi Informasi*, vol. 4, no. 1, pp. 70-76, Jan. 2025, doi: 10.69916/jkbti.v4i1.214.

[7] M. Saputra, V. J. Maulana, D. I. Budiman, and F. Sugiarto, 'Deteksi Awal Penyakit Tanaman Berbasis Citra Daun: Studi Perbandingan Algoritme SVM dan CNN,' 2025.

[8] D. Maharani and B. Hendrik, 'Comparative Study of CNN and SVM for Medical Image Classification,' *Journal of Education Research*, vol. 6, no. 4, pp. 1058-1065, 2025.

[9] G. Annisa and N. Wiliani, 'Perbandingan CNN dan SVM untuk Klasifikasi Penyakit Kulit,' *Teknomatika*, vol. 18, no. 1, pp. 28-36, Jun. 2025, doi: 10.30989/teknomatika.v18i1.1564.

[10] A. Jabbar, D. Mulyawan, L. L. Lestari, and M. Aliyudin, 'Penggunaan CNN untuk Klasifikasi Citra Tumor Otak,' *Jurnal BIIKMA*, 2024.

[11] Q. A'yuni and B. Hendrik, 'SLR: Perbandingan CNN, KNN, dan SVM untuk Klasifikasi Penyakit Kelapa Sawit,' *Journal of Education Research*, vol. 5, no. 4, pp. 6589-6596, 2024.

[12] I P. A. Aryawan, I N. Purnama, and K. Q. Fredlina, 'Klasifikasi Ekspresi Wajah Menggunakan CNN dan SVM,' Universitas Primakara, 2022.

[13] G. P. D. Kisowo, 'Perbandingan Akurasi CNN dan SVM untuk Deteksi Aktivitas Merokok,' Router: *Jurnal Teknik Informatika*, vol. 2, no. 3,

pp. 48-55, Jul. 2024, doi: 10.62951/router.v2i3.145.

[14] T. Liana, et al. “Klasifikasi Citra Daun Teh Menggunakan Deep Learning dengan ResNet Multi-Varian,' *Jurnal Ilmu Komputer*, 2023.

[15] B. K. Gulo, A. R. Himamunanto, and Jatmika, 'Deteksi Penyakit Tanaman Padi Menggunakan SVM dan Random Forest pada Citra Daun,' *Bulletin of Computer Science Research*, vol. 5, no. 4, pp. 724-733, Jun. 2025, doi: 10.47065/bulletincsr.v5i4.660.

[16] K. He, X. Zhang, S. Ren, and J. Sun, 'Deep Residual Learning for Image Recognition,' in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, NV, USA, Jun. 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.

[17] C. Cortes and V. Vapnik, 'Support-Vector Networks,' Machine Learning, vol. 20, no. 3, pp. 273-297, Sep. 1995, doi: 10.1007/BF00994018.

[18] N. Dalal and B. Triggs, 'Histograms of Oriented Gradients for Human Detection,' in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), San Diego, CA, USA, Jun. 2005, vol. 1, pp. 886-893, doi: 10.1109/CVPR.2005.177.

[19] S. Hussain, M. Anwar, and M. Majid, 'Skin Lesion Segmentation and Classification: A Unified Framework of Deep Neural Network Features Fusion and Selection,' *Expert Systems with Applications*, vol. 168, pp. 114401, Apr. 2021, doi: 10.1016/j.eswa.2020.114401.

[20] T. Moen, B. Long, C. M. Chen, D. Bhatt, N. Bhatt, and R. T. Bhatt, 'Deep Learning for Computational Biology,' *Molecular Systems Biology*, vol. 12, no. 7, p. 878, Jul. 2016, doi: 10.15252/msb.20156651.