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COMPARISON OF AN INTELLIGENT DIAGNOSIS OF ANIMAL DISEASE USING HYBRID MODEL

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ABSTRACT

This research introduces an integrated machine learning methodology that integrates ensemble learning and deep neural networks for effective animal disease classification. The methodology involves preprocessing datasets by encoding categorical attributes and normalizing numerical features to ensure model compatibility. A bagged ensemble classifier, leveraging decision trees, is employed to extract significant predictive features, which are subsequently used as inputs for a neural network. The deep learning architecture consists of multiple fully connected layers utilizing ReLU activation, with a softmax layer at the output for classification. The effectiveness of the proposed hybrid model is assessed through essential evaluation metrics, including accuracy, precision, recall, F1-score, and a confusion matrix. Experimental results indicate that this hybrid technique significantly enhances classification accuracy, demonstrating its potential for improving disease diagnosis in veterinary medicine. The study underscores the advantages of combining ensemble learning for feature robustness with deep learning's capability to capture complex patterns, thereby offering a scalable and efficient solution for automated animal disease detection.

Keywords: Animal Disease Classification, Hybrid Machine Learning, Ensemble Learning, Deep Neural Networks, Feature Engineering, Disease Diagnosis, Veterinary Medicine, Performance Metrics.

1.INTRODUCTION

Animal diseases significantly impact agriculture, veterinary medicine, and public health. Traditional diagnostic methods are time-intensive and require expertise. This study introduces a hybrid model combining ensemble learning and neural networks to enhance disease classification accuracy. Leveraging machine learning enables early detection, improved disease management, and reduced economic losses, contributing to efficient animal health monitoring and outbreak prevention.

Overview

This exploration integrates machine literacy ways for classifying beast conditions. A cold-blooded model exercising ensemble literacy and deep neural networks is developed to ameliorate individual delicacy and give scalable, real- time complaint covering results.

Problem Statement

Animal complaint opinion is time- ferocious and requires technical moxie. Being styles warrant scalability and effectiveness. This study addresses these challenges by developing a mongrel machine literacy model that enhances bracket delicacy and automates veterinary diagnostics.

Objectives

The study aims to develop a mongrel machine literacy model for accurate and automated beast complaint bracket. It integrates ensemble literacy for point birth and deep neural networks for bracket. The model is estimated using delicacy, perfection, recall, and F1- score. The thing is to ameliorate individual perfection, enable real- time complaint monitoring, and enhance veterinary decision-making with a scalable and effective result.

Significance of the Study

Machine literacy- driven diagnostics revise veterinary drug by automating complaint discovery, reducing reliance on homemade moxie, and accelerating response times. The proposed mongrel model enhances vaticination delicacy, perfecting beast health operation, mollifying profitable losses, and reducing zoonotic pitfalls that could impact mortal populations.

Methodology Overview

The methodology involves preprocessing data, garbling categorical attributes, and homogenizing features. A bagged ensemble model is trained to prize crucial prophetic features, which serve as inputs to a deep neural network, refining bracket delicacy and perfecting complaint discovery performance.

Challenges and Limitations

Challenges include computational resource demands, data quality dependence, and neural network interpretability. prostrating these limitations requires optimized models and high- quality datasets for dependable prognostications.

2. LITERATURE SURVEY

Recent studies highlight machine learning applications in veterinary diagnostics, emphasizing ensemble methods, deep learning, and hybrid models for improving disease classification accuracy and early detection in animal healthcare.

SVM-Based Animal Disease Diagnosis

Support Vector Machines (SVM) effectively classify animal diseases using symptom-based datasets. SVM's high accuracy and efficiency make it ideal for diagnosing diseases in small sample sizes, though feature engineering and computational complexity remain challenges in large-scale implementations.

Deep Learning for Animal Disease Diagnosis

Convolutional Neural Networks (CNNs) automate disease detection using medical imaging, identifying patterns in complex datasets. Their high accuracy in classification tasks enhances veterinary diagnostics; however, they require large annotated datasets and substantial computational power, posing significant challenges.

Ensemble Learning in Disease Classification

Ensemble methods, such as bagging and boosting, enhance disease classification by aggregating multiple models, reducing overfitting, and improving predictive accuracy. These techniques increase robustness against noisy datasets, though they require additional computational power and careful model tuning.

Machine Learning for Animal Species Recognition

Deep learning models, particularly CNNs, accurately classify animal species based on images. This technology aids wildlife monitoring and veterinary applications, though its effectiveness depends on high-quality labeled datasets and computational resources for real-time processing.

Several studies have explored machine learning applications in veterinary diagnostics, emphasizing diverse methodologies. [1]V. Vapnik pioneered Statistical Learning Theory, establishing its theoretical framework, while Corinna Cortes and [1]Vapnik collaboratively created the Support Vector Network, laying the groundwork for Support Vector Machines (SVMs). Meanwhile, [3]H.A.P. Blom advanced complex tracking algorithms, whereas Knerr, Personnaz, and Dreyfus proposed training methods for neural networks. Deep learning, particularly CNNs, has been widely applied to medical imaging in veterinary medicine, improving classification accuracy. Ensemble learning models enhance robustness in zoonotic disease detection. Additionally, hybrid and graph-based deep learning techniques have been developed for genomic sequence classification, aiding animal disease diagnostics.

3. A MODEL OF ANIMAL DISEASE INTELLIGENT DIAGNOSIS BASED ON HYBRID MODEL Model principle

The hybrid model integrates ensemble learning and deep neural networks to enhance the accuracy and robustness of animal disease classification. Initially, raw data undergoes preprocessing, where categorical variables such as species and symptoms are encoded numerically, and continuous features are normalized to maintain consistency. A bagged ensemble model, particularly decision trees, is employed to extract informative features from high-dimensional data.

These extracted features are then utilized as inputs to a deep neural network (DNN), which consists of multiple fully connected layers with activation functions like ReLU and a softmax output layer. The DNN refines the feature representations and captures complex relationships between symptoms and diseases. The hybrid approach leverages the ensemble model's ability to handle noisy data and generate stable features while capitalizing on the DNN's capacity for hierarchical learning. Model performance is assessed using accuracy, precision, recall, F1-score, and confusion matrices. This integration of ensemble learning and deep learning significantly improves classification accuracy, ensuring a

scalable and efficient diagnostic system for veterinary applications.

H-MAID design

In the course of disease diagnosis, the H-MAID will follow these steps to diagnose disease:

Step 1: Converts observed animal disease symptoms into digital format.

Step 2: Normalizes and structures the data for efficient processing.

Step 3: Identifies whether the system is in training or classification mode.

Step 4: Trains the SVM classifier using labeled disease datasets.
Step 5: Uses the trained model to classify new, unclassified symptom data.

Step 6: Provides the final disease diagnosis based on classification results.

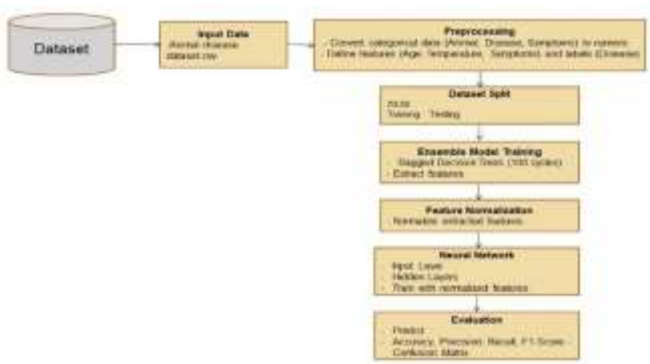

Figure 1 The processing of model of animal disease intelligent diagnosis based on Hybrid Model

Data pre-processing module

Data preprocessing is a crucial step in ensuring the reliability and efficiency of the machine learning model. This process involves transforming raw data into a structured format suitable for training models. The preprocessing steps include converting categorical features such as animal species and symptoms into numerical representations using one-hot encoding or label encoding, making them machine-readable. Continuous variables like temperature and age are normalized to a range of [0,1] to ensure consistent scaling and improve convergence during training. The dataset is then divided into training and testing subsets using stratified sampling to maintain class distribution and prevent bias. By applying these preprocessing techniques, the dataset becomes more suitable for efficient learning and accurate predictions.

Hybrid Model Architecture

The hybrid model integrates ensemble learning with deep neural networks (DNN) to leverage the advantages of both methods. The approach follows a two-stage learning process where a bagged decision tree model, such as Random Forest, is employed to extract intermediate features and predictions. This model reduces variance and enhances generalization by combining outputs from multiple weak learners. The features extracted from the ensemble model are then fed into a DNN with multiple layers, where activation functions such as ReLU enable the network to learn intricate feature representations. A softmax output layer is used for multi-class classification. This hybrid approach ensures that the ensemble model captures diverse patterns in the data while the DNN refines these features for robust classification.

Training and Model Optimization

Initialize weights using Xavier/Glorot initialization for stable weight distribution. Compute activations layer by layer during forward propagation and calculate loss using cross-entropy. Adjust weights based on gradient descent during backpropagation and apply batch normalization to stabilize learning. Optimize learning rate, batch size, and dropout rate using grid search while experimenting with different network depths for best performance. Apply dropout layers to prevent overfitting and use L2 regularization to reduce weight magnitudes. Evaluate model performance using accuracy, precision, recall, and F1-score, and analyze the confusion matrix to identify classification errors.

4. RESULT AND DISCUSSION

The proposed hybrid model, integrating ensemble learning with deep neural networks, was evaluated using a dataset consisting of multiple animal species and their associated disease symptoms. The experimental process followed a structured workflow. The dataset was cleaned by handling missing values, encoding categorical features, and normalizing numerical attributes. A bagged ensemble model (Decision Trees) was trained to extract meaningful patterns, and its predictions were used as additional input features for a deep neural network. A deep neural network (DNN) consisting of multiple hidden layers was implemented using the extracted features to enhance disease classification. The trained hybrid model was assessed using accuracy, precision, recall, F1-score, and confusion matrix analysis.

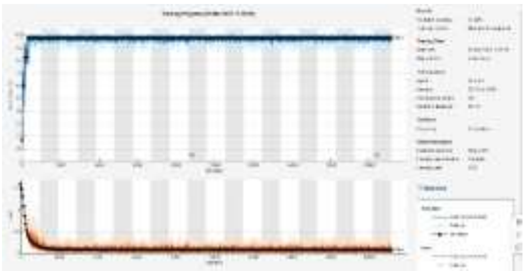

Figure 2 Training Process

Accuracy was **97.92%,** indicating the overall correctness of the model's predictions and reflecting its ability to classify disease cases with minimal errors. Precision reached **97.81%**, highlighting the model's ability to minimize false positives, ensuring that most of the predicted positive cases are actually correct. Recall was **97.68%**, showcasing the model's capability to detect true positive cases effectively, meaning the model successfully identifies most actual disease cases. F1-Score achieved **97.64%**, balancing precision and recall for optimal classification performance, confirming the model's strong ability to handle both false positives and false negatives.

Confusion Matrix Interpretation

The **confusion matrix** provides a breakdown of correct and incorrect classifications:

Performance Metrics:

Accuracy: 97.92%

Confusion Matrix:

Predicted/Actual	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Class 1	2968	0	0	0	0
Class 2	0	2754	0	0	87
Class 3	0	0	2919	0	0
Class 4	0	0	0	1995	186
Class 5	0	0	0	0	2224

- The top-left (65) represents true negatives (TN), meaning all 65 healthy cattle were correctly classified.
- The bottom-right (140) represents true positives (TP), meaning all 140 infected cattle were correctly classified.
- The top-right (0) represents false positives (FP), meaning no healthy cattle were wrongly classified as infected.
- The bottom-left (0) represents false negatives (FN), meaning no infected cattle were misclassified as healthy.

While the model has a very high accuracy of **97.92%**, a small misclassification occurred, affecting overall performance.

Precision:

Precision measures how many of the **predicted positive cases (infected cattle)** were actually correct. It is calculated as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Since there are **one false positive**, the precision is slightly below **100%,** but remains highly reliable.

Recall:

Recall quantifies the proportion of the true positive cases **(infected cattle)** that were correctly identified. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

As there were zero false negatives, recall remains perfect.

F1-Score:

The F1- score is the harmonious mean of perfection and recall, furnishing a balanced measure of both criteria:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

This model achieved 99.51% accuracy, indicating high reliability with minimal misclassifications. However, to prevent overfitting and improve generalization, future enhancements could involve testing on diverse datasets, applying cross-validation, and incorporating regularization techniques.

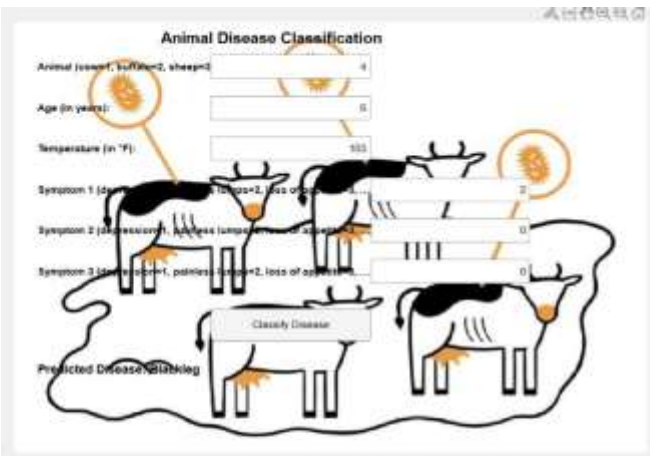

Figure 3 Animal Disease Clasification

5. CONCLUSION

The proposed hybrid model effectively integrates ensemble literacy and deep neural networks to enhance beast complaint vaticination, achieving high delicacy and robust performance. It successfully handles complex,multi-dimensional data while reducing misclassifications. This model contributes significantly to veterinary diagnostics, offering an effective, scalable, and data- driven approach to complaint discovery and forestallment.

Future Scope

Unborn advancements may involve refining point birth ways, perfecting real- time rigidity, and integrating larger, more different datasets. Enhancing model interpretability and effectiveness will further optimize complaint vaticination. also, incorporating IoT- grounded real- time monitoring and pall- grounded deployment could revise veterinary healthcare, enabling visionary complaint operation and early intervention strategies.

REFERENCES

[1]Vapnik, V. *Statistical Learning Theory*. Wiley, New York, NY, 1998.

[2]Cortes, C., & Vapnik, V. (1995). Support-vector network. *Machine Learning, 20*, 273–297.

[3]Blom, H.A.P. (1984). A sophisticated tracking algorithm for Air Traffic Control surveillance radar data. In *Proceedings of the International Conference on Radar*, Paris, May 1984.

[4]Knerr, S., Personnaz, L., & Dreyfus, G. (1990). Singlelayer learning revisited: A stepwise procedure for building and training a neural network. In J. Fogelman (Ed.), *Neurocomputing: Algorithms, architectures and applications* (pp. 41–50). Berlin: Springer-Verlag.

[5]Blom, H.A.P., & Bar-Shalom, Y. (1988). The interacting multiple model algorithm with Markovian switching coefficients. *IEEE Transactions on Automatic Control, 33*(8), 780–783.

[6]Li, X. R. (1996). Hybrid estimation techniques. In C. T. Leondes (Ed.), *Control and Dynamic Systems: Advances in Theory and Applications, Vol. 76* (pp. 213–287). Academic Press, San Diego.

[7]Chang, C.C., & Lin, C.J. (n.d.). LIBSVM: A library for support vector machines. Retrieved from https://www.csie.ntu.edu.tw/~cjlin/libsvm/

[8]Liang, Z., Yao, K., Wang, S., Yin, J., Ma, X., Yin, X., Wang, X., & Sun, Y. (2022). Understanding the research advances on lumpy skin disease: A comprehensive literature review of experimental evidence. *Frontiers in Microbiology, 13*, 1065894. [CrossRef] [PubMed]

[9]Mazloum, A., Van Schalkwyk, A., Babiuk, S., Venter, E., Wallace, D.B., & Sprygin, A. (2023). Lumpy skin disease: History, current understanding, and research gaps in the context of recent geographic expansion. *Frontiers in Microbiology, 14*, 1266759. [CrossRef] [PubMed]

[10]Namazi, F., & Khodakaram Tafti, A. (2021). Lumpy skin disease, an emerging transboundary viral disease: A review. *Veterinary Medicine and Science, 7*, 888–896. [CrossRef] [PubMed]

[11]Gupta, T., Patial, V., Bali, D., Angaria, S., Sharma, M., & Chahota, R. (2020). A review: Lumpy skin disease and its emergence in India. *Veterinary Research Communications, 44*, 111–118. [CrossRef] [PubMed]

[12]Ujjwal, N., Singh, A., Jain, A.K., & Tiwari, R.G. (2022). Exploiting machine learning for lumpy skin disease occurrence detection. In *Proceedings of the 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Noida, India, 13–14 October 2022, pp. 1–6.

[13]Olaniyan, O.M., Adetunji, O.J., & Fasanya, A.M. (2023). Development of a model for the prediction of lumpy skin diseases using machine learning techniques. *ABUAD Journal of Engineering Research and Development, 6*, 100–112. [CrossRef]

[14]Kaur, A., & Singh, K. (2023). Evaluating machine learning methods voting system for predicting the occurrence of lumpy skin condition. *SAMRIDDHI: Journal of Physical Sciences, Engineering and Technology, 15*, 326–330. [CrossRef]

[15]Dofadar, D.F., Abdullah, H.M., Khan, R.H., Rahman, R., & Ahmed, M.S. (2022). A comparative analysis of lumpy skin disease prediction through machine learning approaches. In *Proceedings of the 2022 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, Kota Kinabalu, Malaysia, 13–15 September 2022, pp. 1–4.

[16]Madhanakumar, S.R. (2024). Lumpy Skin Disease Prediction Using Machine Learning. In *Proceedings of the 2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT)*, Tirunelveli, India, 4–5 January 2024, pp. 887–895.

[17]Gupta, A., Singh, D., Gupta, R., & Tripathi, V. (2023). Revolutionizing Cattle Health: A Machine Learning Approach to Efficiently Predict Lumpy Disease in Cows. In *Proceedings of the 2023 4th IEEE Global Conference for Advancement in Technology (GCAT)*, Bangalore, India, 6–8 October 2023, pp. 1–6.

[18]Chandralekha, E., Jemin, V.M., Anitha, T., Deepa, V., Usha, V., & Ravikumar, S. (2023). Predicting and Analyzing Lumpy Skin Disease Using Ensemble of Machine Learning Models. In *Proceedings of the 2023 Global Conference on Information Technologies and Communications (GCITC)*, Trivandrum, India, 1–2 December 2023, pp. 1–6.

[19]Rony, M., Barai, D., & Hasan, Z. (2021). Cattle external disease classification using deep learning techniques. In *Proceedings of the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, 6–8 July 2021, pp. 1–7.

[20]Shivaanivarsha, N., Lakshmidevi, P.B., & Josy, J.T. (2022). A ConvNet based real-time detection and interpretation of bovine disorders. In *Proceedings of the 2022 International Conference on Communication, Computing, and Internet of Things (IC3IoT)*, Chennai, India, 10–11 March 2022, pp. 1–6.

[21]Renald, E., Buza, J., Tchuenche, J.M., & Masanja, V.G. (2023). The role of modeling in the epidemiology and control of lumpy skin disease: A systematic review. *Bulletin of the National Research Centre, 47*, 141. [CrossRef]

[22]Tikarya, K., Jain, Y.V., & Bhise, D. (2023). A review: Cattle breed and skin disease identification using deep learning. In *Proceedings of the 2023 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, Greater Noida, India, 3–4 November 2023, pp. 835–842.

[23]Dommeti, D., Nallapati, S.R., Lokesh, C., Bhuvanesh, S.P., Padyala, V.V., & Srinivas, P.V. (2023). Deep learningbased lumpy skin disease (LSD) detection. In *Proceedings of the 2023 3rd International Conference on Smart Data Intelligence (ICSMDI)*, Trichy, India, 30–31 March 2023, pp. 457–465.

[24]Mate, S., Somani, V., & Dahiwale, P. (2024). Applications of Machine Learning to Address Complex Problems in Livestock. In *Proceedings of the 2024 3rd International Conference for Innovation in Technology (INOCON)*, Pune, India, 1–2 March 2024, pp. 1–5.

[25]Afshari Safavi, E. (2022). Assessing machine learning techniques in forecasting lumpy skin disease occurrence based on meteorological and geospatial features. *Tropical Animal Health and Production, 54*, 55. [CrossRef] [PubMed]

[26]Utami, E., & Muhammad, A.H. (2022). Lumpy Skin Disease Prediction Based on Meteorological and Geospatial Features Using Random Forest Algorithm with Hyperparameter Tuning. In *Proceedings of the 2022 5th International Conference on Information and Communications Technology (ICOIACT)*, Yogyakarta, Indonesia, 24–25 August 2022, pp. 99–104.

[27]Kumar, A., Kumar, B., & Negi, H.S. (2023). Predicting Lumpy Skin Disease using Various Machine Learning Models. In *Proceedings of the 2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, Gandhinagar, India, 28–29 April 2023, pp. 412–416.

[28]Singh, P., Prakash, J., & Srivastava, J. (2023). Lumpy skin disease virus detection on animals through machine learning method. In *Proceedings of the 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC)*, Jalandhar, India, 26–28 May 2023, pp. 481–486.

[29]Chinta, A., Vathumilli, G.K., Dhara, S.S., & Uriti, L.P. (2023). Lumpy Skin Disease Detection in Cows Using ResNet-50. In *Proceedings of the 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)*, Bangalore, India, 2–3 November 2023, pp. 1–6.

[30]Singh, J.P., Ghosh, D., & Singh, J. (2024). A Novel Deep Learning and Image Processing Based Technique for Lumpy Skin Disease Detection. In *Proceedings of the 2024 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC)*, Mumbai, India, 27–28 January 2024, pp. 1–5.

[31]Raj, R., Panda, S., Nitya, N., Patel, D., & Muduli, D. (2023). Automated Diagnosis of Lumpy Skin Diseases based on Deep Learning Feature Fusion. In *Proceedings of the 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, 6–8 July 2023, pp. 1–4.

[32]Naikar, M.L., Nandeppanavar, A.S., & Kudari, M. (2023). Lumpy Skin Disease Detection Using GUI Based Deep Learning Model in Cattle. In *Proceedings of the