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Chicken Disease Detection in the Poultry Utilizing Grey Wolf Optimized Deep Convolutional Neural Network

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Abstract

Poultry production is very essential across the world and helps to provide high nutrients and proteins to human beings through meat and eggs. Though the farmers can save money from the poultry as it needs only a limited amount of resources to feed the chicken, a heavy loss occurs in the poultry due to the fast spread of disease among the chicken that may not be controlled by humans. Recently many technologies have been developed to detect chicken disease, but the technologies faced certain issues such as increased time consumption, inefficient detection, and so on. To defeat the mentioned challenges, a proposed method named Grey wolf optimized Deep Convolutional Neural Network (GWO-Deep CNN) is designed to enrich the performance of research by detecting the disease accurately and further helps veterinarians to diagnose the disease properly, which reduces the death rate among the chickens in the poultry. The Deep CNN is utilized effectively to detect the disease accurately and classify the detected disease. Performance metrics utilized to analyze the performance of the GWO-Deep CNN are accuracy, sensitivity, and specificity, which attain 0.973, 0.983, and 0.965 respectively.

Keywords: Poultry chicken disease, Grey Wolf Optimization, Deep Convolutional Neural Network, Structural descriptor, Ranking Approach.

1 Introduction

The world populations obtain enriched food from animals that contain heavy protein and nutrients. Animal products are helpful for people of all ages to stay healthy in their lives and satisfy the demands of people throughout the world. Recently a report has been generated to show the growth of poultry farming worldwide [15]. Poultry farming needs only a limited amount of resources that consume low money values, which is the main advantage of increasing poultry farming. Secondly, poultry contributes to all types of climates compared to cattle farming [29] [4]. The quality of poultry farming is determined by the foods which humans feed to the animals [1]. A major issue concern in poultry farming is disease, once the disease affects the poultry it spreads to all chickens resulting in high loss to the farmer, which poses a danger to human health because the person who takes the meat of the diseased chicken, the disease in the chicken spread to human [17] [2]. The Spread of disease in the chicken and the losses are prevented by detecting the chicken sick [16] early by labeling and classifying the chicken based on their behaviors, so a monitoring system is placed in the poultry [30] [31] [3].

The video and sound monitoring mechanisms offer many benefits that provide a monitoring service for 24 hours, which reduces the chicken infection risk. In addition, further, the method was implemented to classify chicken diseases and identify the severity of the diseases based on the recognition rate. However, the accuracy of the outcome needs to improve in the research [18] [2]. Recently, the You Only Look Once (YOLO-V3) object detection algorithm and ResNet50 image grading model for the detection and classification of poultry disease from chicken. The designed model was implemented to attain easy access for veterinarians and farmers in the poultry. However, the system that not tell the type of disease accurately, so the performing task of the system was not efficient absolutely [1]. In addition, another method named chicken sound convolutional neural network (CSCNN) recognizes the sound of the chicken and identifies the healthy and infected chicken. Certainly, the system reduced redundant information computation and certain noise influences. However, the system that identified later, so the death rate was raised and the performing task of the method was not enhanced in the model. The Generative Adversarial Networks (GAN) predict chicken health by utilizing the classification of machine learning (ML) techniques. The implemented model provided accurate predictions of the chicken disease, so the performing task of the method was enhanced in the system investigation [3]. Even though, the system could not predict the disease of the chicken individually, need certain tools, so the efficiency was reduced in the research.

Along with the feature extraction, the research enables poultry disease detection with the GWO-Deep CNN model. ResNet-101 is utilized as one of the feature extraction mechanisms to reduce the percentage of error and enhance the ability of the Deep CNN. Further, the ranking approach is utilized to prioritize the features in the image and reduce the dimensions of the image to achieve better performance[34]. A deep CNN classifier is utilized to enhance the performance and reduce the time during the computational process, and further implementing the GWO-Deep CNN to provide an enriched efficiency in the research.

- **Grey Wolf Optimization:** GWO-Deep CNN attains better efficiency by breaking the complex problem into sub-sections, increasing the performance of the system, reducing the timing consumption, and reducing the errors.
- **Grey Wolf Optimized enabled Deep Convolutional Neural Network (GWO-Deep CNN):** The GWO-Deep CNN method identifies the chicken disease accurately by recognizing the image for which the features are automatically extracted in the research. The proposed method provides an effective result that shows whether the chicken is affected by the disease or not and further classifies the disease detection through the model.

The system investigation is organized as section, the assessed convolutional techniques in section 2, the sketch of the disease detection in poultry utilizing GWO-Deep CNN is detailed in section 3, the result section of the research is detailed in the section 4, and the last section is referred as a conclusion part in section 5.

2 Literature Review

Mizanu Zelalem Degu *et al.* [1] designed a YOLO-V3 object detection algorithm and ResNet50 image classification model for the detection and classification of poultry disease from chickens. The designed model was implemented to attain easy access for veterinarians and farmers in poultry. However, the system did not tell the type of disease accurately, so the performing task of the systematic investigation was in efficient absolutely.

Kaixuan Cuan *et al.* [2] demonstrated a CSCNN that detected the sound of the chicken through which the healthy and diseased chicken is identified in the system. In addition, the system reduced redundant information and certain noise influences. Moreover, the CSCNN detected the disease later, which resulted in an increased death rate that showed that the performance was not enhanced in the research.

Ghufran Ahmed *et al.* [3] implemented GAN to enlarge the dataset, in which the ML classification was utilized to classify the healthy and unhealthy chickens from the poultry. The implemented model provided accurate predictions in chicken disease, so the performing task of the model was enhanced in the research. The system could not predict the disease of the chicken individually without certain advanced tools that resulted in poor detection performance.

Suresh Neethirajan *et al.* [4] utilized Yolov5, which detected the trajectories of the chicken in the poultry by mapping the designed modules in the system. Similarly, the model could track the trajectories of multiple chickens, which enriches the ability of the system. The systematic investigation addressed the challenge as, the model could not predict the disease accurately, which reduced the efficiency of the research.

Zengxu Song *et al.* [5] drew out a sandwich enzyme-linked immunosorbent assay (ELISA) to analyze the risk assessment of the infected chickens. The drawn-out model ensured food safety after identifying the disease in the chicken that resulted in low-cost production and high throughput respectively. Similarly, the model's efficiency and accuracy needed to be improved in the research.

The above review describes that the model implemented till now are not very efficient to detect diseases in chickens. Therefore, this research focuses on the optimized deep learning model that will identify the diseases. To optimize the model

Grey wolf optimization is the most widely used metaheuristic algorithm. GWO-Deep CNN attains better efficiency by breaking the complex problem into sub-sections, increasing the performance of the system, reducing the timing consumption, and reducing the errors. The various prior studies that used GWO and deep CNN to diagnose illnesses are described in Table 1.

Table 1. Various types of Disease Identification using GWO with Deep CNN

Reference	Year	Objective	Model	Strength	Measurement
Naik, N. K. et.al [36]	2024	Primitive Indian Paddy Grain Identification	CNN	The recognition rate on a limited training dataset is improved, and 2D-DWT enhanced the feature vector's dimension	Accuracy - 98.50 % Sensitivity - 98.50% Specificity- 99.83% Precosion- 98.56 % F1 score of 98.50 %,
Abuya, T. K. et al.[37]	2024	Lung Cancer Prediction	For classification CNN, Random Forest (RF), and Decision Trees (DT)	Model performance enhanced by using GWO	Accuracy 96%
Liu, L. et al [38]	2024	Skin Lesion Ensemble Classification	Four distinct ensemble strategies	By using GWO effectively avoids the premature convergence problem and improves the search combination efficiency	Accuracy -88.8% Precision- 83.7% Recall-89.7% F1 scores -86.2%
Sharma, D. K. et al.[39]	2024	Sugarcane Diseases Detection	CNN	By using GWO, model performance, improved	Accuracy - 84.74% Precision- 63.63% Recall-93.33% F1 scores - 75.88%
Sharmila , V et al.[40]	2024	Skin Lesions Detection	CNN	The accuracy has improved using GWO.	Accuracy -96.5% Precision - 97% Specificity - 96.2%

					Sensitivity - 92.1%
Seetha, J. et al.[41]	2023	Mango Leaf Disease Classification	CNN	The accuracy has improved.	Accuracy - 96.7111% Precision - 97.5712% Recall - 97.1504% F1 Score - 96.4792%
Bilal, A. et al.[42]	2022	Diagnose Diabetic Retinopathy.	CNN	Its capability to ensure rapid convergence by balancing effective exploration and exploitation during the search process.	Accuracy to 98.33%
Gopatoti, A. et al.[43]	2022	COVID-19 Diagnosis	Deep Learning CNN	The model design is checked for optimality using the grey wolf optimization technique.	Accuracy - 94.00% for the 4-class model Accuracy 97.05% for the 3-class model 100% accuracy for Model
Gülmez, B. [44]	2023	Cotton Disease Detection	CNN	Model performance enhanced.	Accuracy- 100%
Sallam, N. M. et al.[45]	2022	Blood Diseases Detection	K-nearest neighbors (KNN), support vector machine (SVM), naïve Bayes (NB), RF	Select useful features and enhance performance.	Accuracy- 99.69%

Mohakud, R. et al.[46]	2021	Skin Cancer Detection	CNN	Efficiency has boosted using GWO.	Accuracy-98.33%

2.1 Challenges

- The SVM did not find accurate data with major predictive information about the chicken, which was relevant to describing the disease in the poultry [26].
- The multi-posture and the multi-behaviour of chicken recognition were not captured for the diagnosis of disease in the chicken [28].
- The CNN was simple and had high speed in training that detects on type of chicken disease named avian influenza, the other disease cannot be identified in the research [2].
- The Deep CNN could not expand the dataset and was not utilized in the stage of emergency to detect the disease of the chickens [29].

3 Methodology

The target of the research is to detect poultry disease by employing the GWO-Deep CNN. In the research, the input image is taking over from the Poultry Disease Diagnostics dataset [32] and the Farm labeled fecal images dataset [33]. The input data is fed into the preprocessing that improves the image by removing the distortion in the image and ROI extraction extracts the relevant region of the image. After all the features are preprocessed, the extracted image is entered into the feature extraction that contains structural descriptor and ResNet-101 that defines the structure and extracts the image based on the relevant features for further process. Then the extracted feature of the image passes into the Ranking approach which acts as the feature selection process and reduces the dimensions of the image to improve the performing task of the image. Finally, the image passes into the GWO-Deep CNN that minimizes the computation, classifies the image with high accuracy, and detects healthy and sick chickens in poultry. The detailed description of the systematic investigation is sketched out in Figure 1.

3.1 Input Image

The fecal input image is fetched from the poultry disease diagnostic dataset [30] and Farm labeled fecal images [31]. The dataset includes 6812 files, organized as four classes of disease stored in four categories, which are labeled in accurate order. The input image is represented as S_a,

$$S = \{S_1, S_2, \ldots\ldots, S_a, \ldots\ldots, S_S\} \tag{1}$$

where, S_a is represented as the input image in the dataset S, S_S is represented as the total number of inputs in the dataset.

3.2 Preprocessing

The image is efficiently improved in the preprocessing by enhancing the features and eliminating the distortions [6]. The ROI extraction is utilized to extract the significant region in an image [7].

The preprocessing is symbolized as S^*_a .

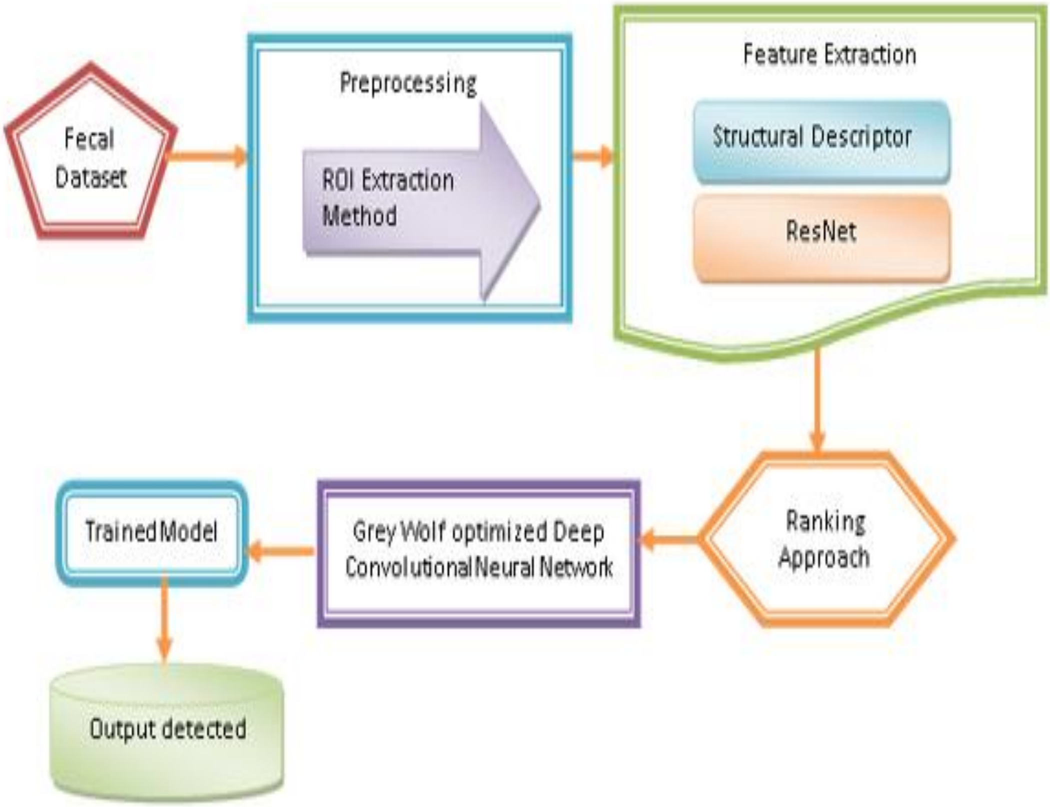


Figure 1. Block Diagram of GWO-Deep CNN

3.3 Feature Extraction

The selected relevant information of the feature extraction is viewed in an image and reduces the dimensionality of the image [8]. The feature extraction process includes structural descriptor and ResNet-101 that are described below,

3.3.1 Structural Descriptor

Structural descriptors are utilized to define the structures that are grouped to identify the majority of the sub-parts, which have a similar structure and spatial distribution [9].

3.3.1.1 Local Binary Pattern (LBP)

LBP is utilized in the image feature extraction to produce a better statistical texture of an image. The distinct shaped images are captured with different orientations that hold the inter-class variations, which are reduced here to obtain the précised image [11]. LBP is calculated [22] as follows,

$$C_{M,N} = \sum_{b=0}^{b-1} S_a^*(d_e - d_h)2^b \tag{2}$$

$$S_a^{\;*}(y)=\begin{Bmatrix}1, y\geq 0\\ 0, y<0\end{Bmatrix} \tag{3}$$

where, d_h is the central pixel gray value, d_e is the neighbor's value, M is represented as the total number of the neighbors involved, N is represented as the neighbor radius, 2^b is the binomial weight, and $C_{M,N}$ is the output of LBP.

3.3.1.2 Canny Edge

The canny edge detection algorithm smoothens the image by utilizing a Gaussian filter and reduces the noise effect by calculating the image to obtain the edge response. The gradient of the image is calculated by obtaining the neighboring area of the image [12]. The canny edge is calculated below as [23],

$$Y=\frac{1}{2\prod\sigma^2}\exp\left(-\frac{u^2+v^2}{2\sigma^2}\right) \tag{4}$$

where, v is the vertical axis distance from the origin and u is the horizontal distance from the origin of the image $S_a^{\;*}$. σ is represented as the Gaussian distribution standard deviation, and Y is represented as output of a canny edge.

The LBP and Canny edge are concatenated to form a structural descriptor, which is calculated as, SD, as follows,

$$SD=[C_{M,N}\,\|\,Y] \tag{5}$$

3.3.2 ResNet-101

The feature extraction is further obtained through the ResNet 101 model, which contains 101 convolutional layers [19]. Initially, the resolutions are reduced to extend the channel and then perform further process [21]. ResNet-101 is utilized numerous of filters to capture expensive features and the convolutional layers, then the parameters are reduced on the edge region. To avoid the missing image features, the influence of the noise is reduced from the background [20]. In addition, the ResNet 101 decreases the difficulties that are faced at the time of training and to define the identity mapping [10]. The outcome of ResNet 101 is determined as, RS .
Finally, the features obtained from the Structural descriptor and ResNet-101 are combined to produce feature vector, which is described as,

$$DE=\left[SD\,\|\,RS\,\right] \tag{6}$$

3.4 Ranking Approach as Feature Selection

The ranking approach acts as the feature selection mechanism to reduce the feature dimensions of the image by utilizing the final feature vector. In addition, the ranking approach easily separates the positive and negative values by minimizing the feature vector dimensionality and boosting the performance of the classification [13].

$$F=\left\{DE_v\right\}_{[A\times B]} \tag{7}$$

Where, DE represents the features that are extracted from the structural descriptor, and ResNet 101 in the fecal images, v^{th} represents the obtained fecal image.

$$AB(DE_v) = X\{DE_v(k,t)\}_{J_{\max}} \tag{8}$$

where, k and t represent the vector features, and $X\{DE_v(k,t)\}$ represents the integrations of different features DE shown in equation (6), the combinations of feature are elaborated as,

$$AB(DE_v) = \{DE_v{}^{12}, DE_v{}^{13}, \ldots, DE_v{}^{21}, DE_v{}^{23}, \ldots, DE_v{}^{31}, DE_v{}^{32}, \ldots, DE_v{}^{zy}\}_{J_{max}} \tag{9}$$

The equation (8) is generalized as,

$$AB(DE_v) = \{DE_v{}^{yz}\}_{J_{\max}}^{(z,y=1,2,..e)\&z\neq z} \tag{10}$$

To establish the classification model maximal score is selected for the feature combination. The combination of the features is passed into the Deep CNN classifier and produces the outcome as, $J_{1,2,3,\ldots.e}$

$$rank = Max\left(J_{(J_1,J_2,\ldots J_Z)}\right) \tag{11}$$

The above-mentioned equation (10) represents the ranking-based feature selection.

3.5 Poultry disease detection using GWO Deep CNN

The poultry disease detection utilizes GWO Deep CNN to attain accurate detection with highly efficient classified outcomes. In addition, Deep CNN captures the image automatically for detecting the disease in the chicken [25]. Deep CNN has multiple layers, which are utilized to process the extracted features that consume only very less power during the time of the computational process [24].

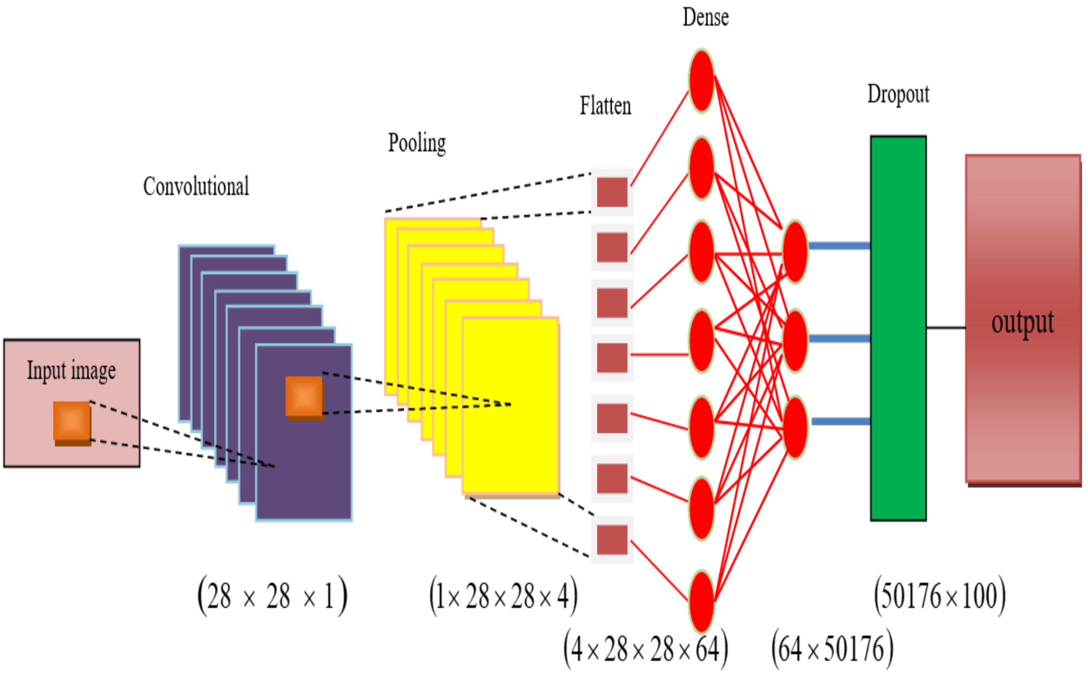


Figure 2. Architecture Diagram of Deep CNN

Deep CNN contains a multi-convolutional layer, initially, the feature vector input size is ($1\times 28\times 28\times 1$) fed into the convolutional layer, and the block contains seven convolutional layers along with max-pooling that extracts the feature vector[35]. Then the feature vector passes into the max pooling with the size $(1\times 28\times 28\times 4)$ that reduces the dimensions by selecting the maximum value from the region. The output of the max pooling layer of size $[1\times 28\times 28\times 64]$ is passed as an input into the flatten layer that extracts the spatial features from the layer which are connected fully, with the size of the output (1×50176). At last, the result of the flattened layer pass into the dense layer, the dense layer that classifies the disease and the layer produces an efficient output size (1×100).

3.6. Grey Wolf Optimization

Grey wolf characteristics such as tracking, encircling, and attacking prey, are well-trained to attain the best-performing task in the CNN classifier. The GWO addresses certain advantages collate with other quality mechanism such as which mimic the effective hunting techniques of a pack and fewer parameters are present so it is easier to implement the techniques rapidly.

3.6.1 Inspiration

Tracking, encircling, and attacking are the characteristics [14] of the grey wolf, belonging to the Canidae family. The grey wolf lives as a pack, average size is 5-12. Grey wolf allot a leader for themselves; leaders are male and female, named as alphas. In addition, the grey wolf makes decisions only by considering the alpha about sleeping, hunting, and so forth. The other name of the alpha wolf has the power because the entire wolf in the pack should follow the alpha wolf command. The second category of grey wolf is a subordinate wolf that helps in the time of decision making, named as beta. Simultaneously, the beta conveys the commands of alpha to the entire pack and provides reviews about the command. The last level of grey wolf ranking is omega which is considered as the last wolf that plays the character of scapegoat. If any of the wolf is not in the mentioned three groups then the wolf is named as a delta that dominates the omega. In the case of any danger that occurs in their regions, scouts warn the pack because scouts are responsible for taking care of the boundaries. Hunters in the pack help to hunt the prey and provide food to the pack. The Caretaker’s wolf cares for the weak wolf in the pack. Thus, the solutions of the optimization are elaborated as follows,

Initialization

The weight and bias of the initialization are mentioned below:

$$Z=[\phi,\delta] \tag{12}$$

where, ϕ,δ describe the bias and weight.

Declaration of an Object function

Object function declares maximization function to the utilized optimization. Object function is denoted as I,

$$I=Max(Accuracy) \tag{13}$$

Solution update

The updated solutions as per the behavior of hunting and attacking characteristics of the grey wolf, are described below,

Search for prey

Grey wolf search for prey according to their position, $|R > 1|$ and grey wolf force the prey and identify the prey, which is fitter respectively.

$$G\vec{H} = \left|\vec{A}.\vec{B}_z(i) - \vec{B}(i)\right| \tag{14}$$

$$\vec{B}(i+1) = \vec{B}_z(i) - \vec{A}.G\vec{H} \tag{15}$$

where, i represents the iteration in current, $\vec{R}$ and $\vec{A}$ are the vector coefficients, $\vec{B}_z$ is the vector position of the prey, $G\vec{H}$ is described as the solution position, and $\vec{B}$ describes vector grey wolf position.

The vectors $\vec{R}$ $\vec{A}$ are calculated below,

$$\vec{R} = 2\vec{q}.\vec{o}_1 - \vec{q} \tag{16}$$

$$\vec{A} = 2.\vec{o}_2 \tag{17}$$

where, $\vec{q}$ is linearly minimized from 2 to 0 over the iteration of the course, and o_1, o_2 are the random vectors in the range $[0,1]$.

$$G\vec{H}_\alpha = \left|\vec{A}_1.B_\alpha - \vec{B}\right|, G\vec{H}_\beta = \left|\vec{A}_2.B_\beta - \vec{B}\right|, G\vec{H}_\delta = \left|\vec{A}_3.\vec{B}_\delta - B\right| \tag{17}$$

$$\vec{B}_1 = \vec{B}_\alpha - \vec{R}_1.\left(G\vec{H}_\alpha\right), \vec{B}_2 = \vec{B}_\beta - \vec{R}_2.\left(G\vec{H}_\beta\right), \vec{B}_3 = \vec{B}_\delta - \vec{R}_3 \vec{.}\left(G\vec{H}_\delta\right) \tag{18}$$

$$\vec{B}(i+1) = \frac{\vec{B}_1 + \vec{B}_2 + \vec{B}_3}{3} \tag{19}$$

Attacking Prey

To attack the prey certain conditions are followed, which force the wolf to perform a hunt. The position of the search agents is updated by the position of alpha, beta, and delta. The condition $|R| > 1$ of the grey wolf forces prey that find the fitter prey hopefully.

4 Results and Discussion

The paper implements the GWO-Deep CNN for poultry disease detection and the main purpose of the model that enrich the accuracy. The section mentioned the estimation of the result of poultry disease detection in the Deep CNN optimizer.

4.1 Experimental setup

Experiment is implemented in the Python software of the system configuration of Windows 10 and the storage capacity is concerned with 16 GB ROM.

4.2 Dataset Description

The poultry Disease Diagnostics [32] and Farm labeled fecal images [33] are employed in the systematic investigation of poultry disease detection with GWO-Deep CNN. The images contain the healthy and coccidiosis disease captured in the poultry farms. The chicken disease named salmonella is captured from the poultry farm after spreading for 1 week. Another disease named Newcastle that captured within three days.

4.3 Experimental analysis

The results image of the systematic investigation is described below in Figure 3,

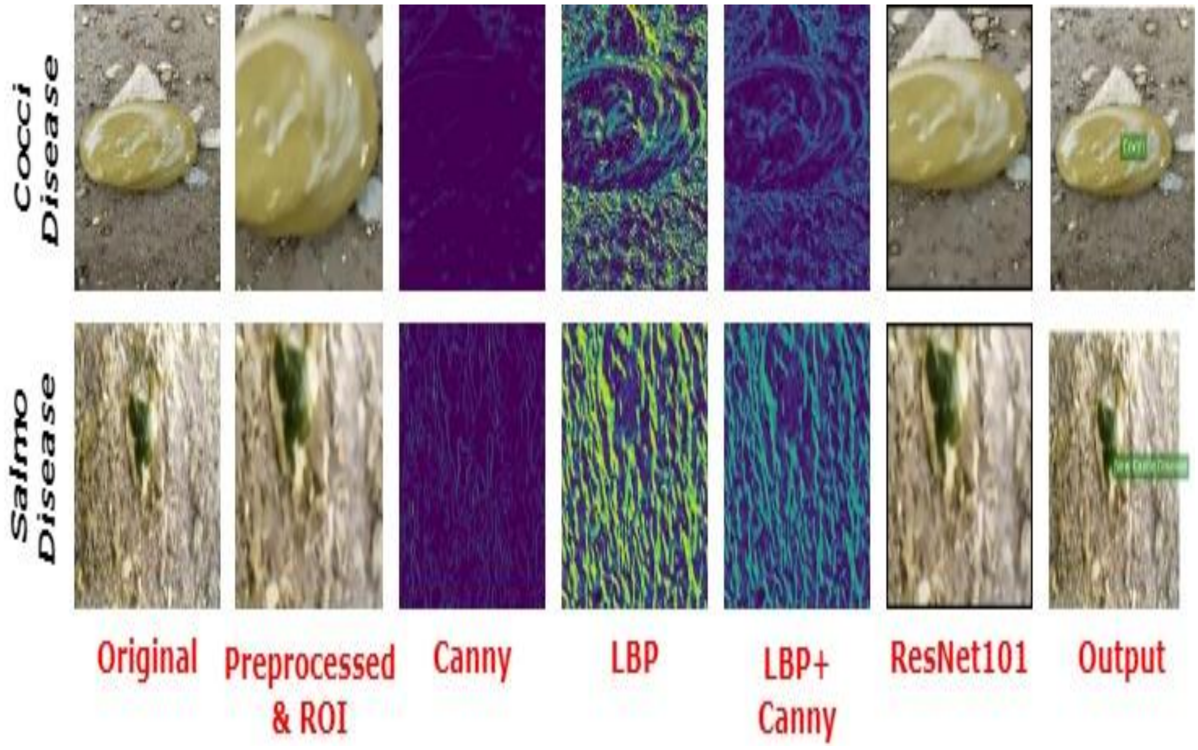


Figure 3. Experimental Results of GWO-Deep CNN in Chicken Poultry Disease Detection

4.4 Performance Metrics

The outcome performance metrics are described below.

Accuracy: The exact disease image is identified in the systematic investigation and is mentioned as (A).

$$A = \frac{Q_{tp} + Q_{tn}}{Q_{tp} + Q_{tn} + Q_{fp} + Q_{fn}} \tag{20}$$

where, Q_{tp} represent the true positive, Q_{tn} represent the true negative, Q_{fp} represent the false positive, and Q_{fn} represent the false negative.

Sensitivity: The sensitivity evaluates the capability to detect the poultry disease in all categories and which is mentioned as (W).

$$W = \frac{Q_{tp}}{Q_{tp} + Q_{fn}}, \tag{21}$$

Specificity: The specificity evaluates to detect appropriately and provides the outcome which is represented negatively in the model and which is mentioned as (K).

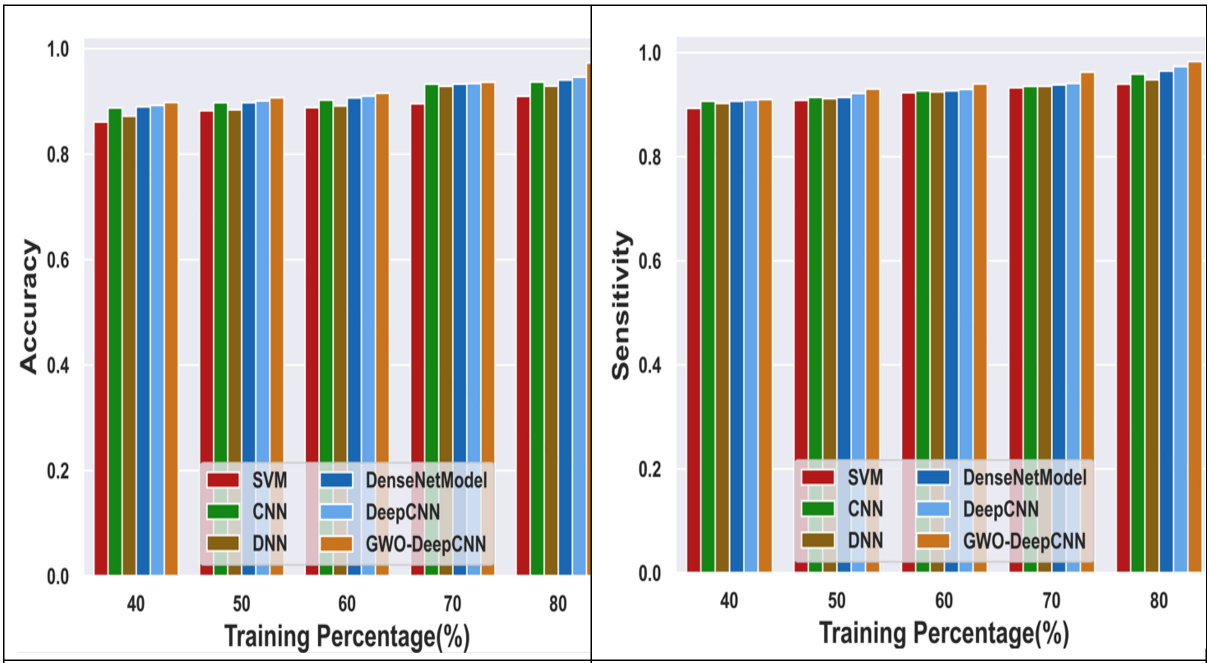
$$K = \frac{Q_{tn}}{Q_{tn} + Q_{fp}}, \tag{22}$$

4.5 Comparative Evaluation

The GWO-Deep CNN model concerns the metrics and comparatively evaluated and shown respectively. The GWO-Deep CNN model compare with the existing methods such as Support Vector Machine (SVM), Convolutional Neural Network (CNN), Deep Neural Network (DNN), DenseNet, and Deep Convolutional Neural Network (Deep CNN)

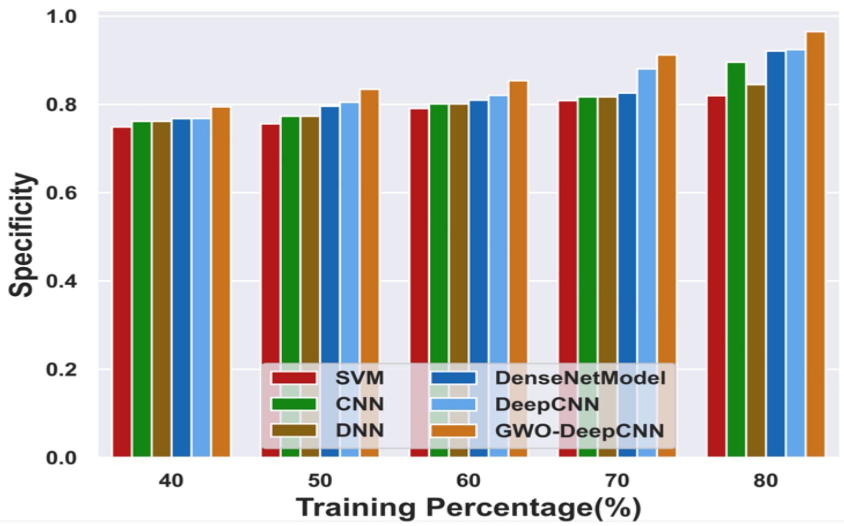
4.5.1 Comparative evaluation of Farm labeled fecal images with TP

The chicken disease detection with the GWO-Deep CNN model is utilized in the farm-labeled fecal dataset and is compared with the existing mechanisms. The accuracy of the model is improved by 3.29%with the SVM, and 4.52% with CNN. The model's sensitivity is improved by 3.56% with the CNN, and 2.44% with DNN with the previous method. The specificity of the model is improved by 15.03% with the Dense Net, and 4.25% with Deep CNN with the traditional method. The figure 4 represents the comparative evaluation and placed absolutely.



Accuracy

Sensitivity

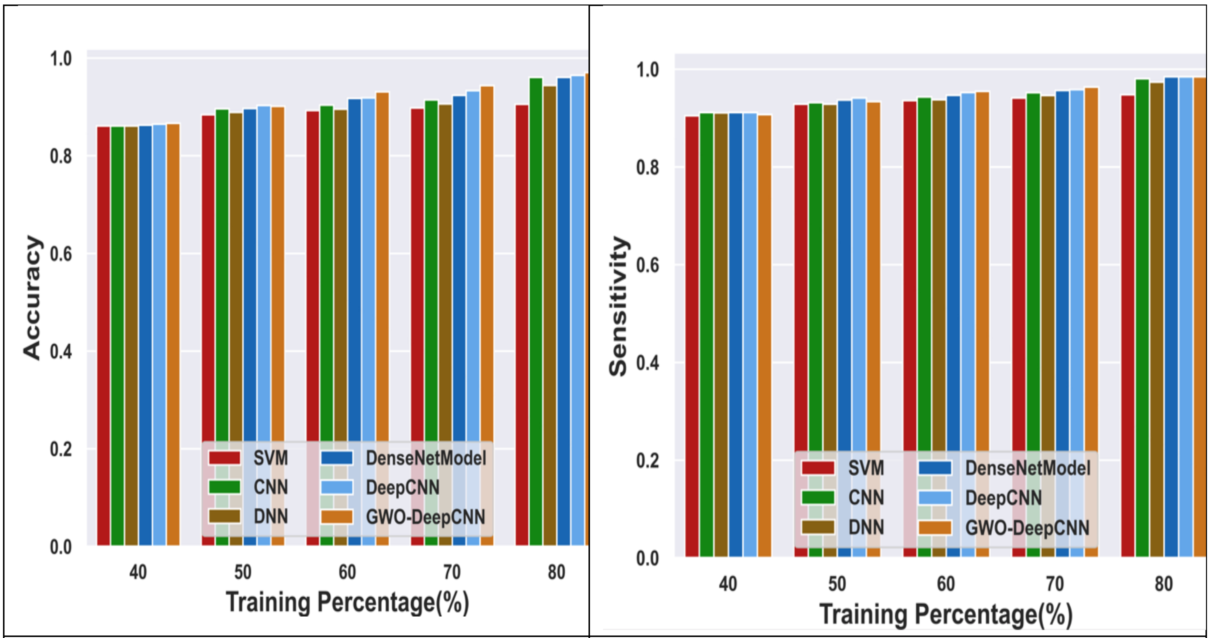


Specificity

Figure 4. Comparative evaluation with Form labeled fecal images

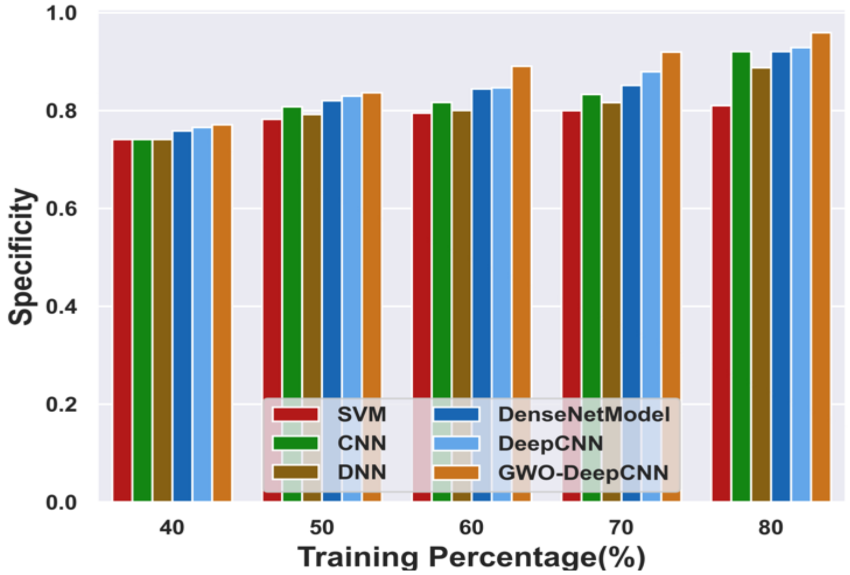
4.5.2 Comparative Evaluation of Poultry Diseases Diagnostics fecal images

The comparative analysis of the poultry chicken disease detection with the GWO-Deep CNN model is utilized in the Poultry Disease Diagnostics dataset of a TP. Accuracy of the model is improved by 1.03% with SVM, and 2.78% with CNN. The model's sensitivity is improved by 0.41% with the DNN, 1.12% with CNN, and 3.76% with DenseNet. The specificity of the model is improved by 7.40% with CNN, and 3.13% with Deep CNN with the previous method. The comparative analysis of the K-fold is measured in Figure 5.



Accuracy

Sensitivity



Specificity

Figure 5. Comparative evaluation of Poultry Disease Diagnostic

4.6 Comparative Discussion

The GWO-Deep CNN model is utilized to compare with the existing techniques, the SVM [26] cannot able to provide an accurate disease detection outcome when the dataset is large in the research. The CNN [27] needs much time for training and produces the disease detection outcome as slow. The DNN [4] needs a high amount for the training process. The DenseNetModel [28] requires numerous parameters to become expensive. The Deep CNN [29] considers only the feature detail as an input. The comparative discussion of GWO-Deep CNN is employed in Table 1.

Table 1: Comparative discussion of the GWO-Deep CNN model

Analysis/Methods			**SVM**	**CNN**	**DNN**	**DenseNetModel**	**Deep CNN**	**GWO-Deep CNN**
TP	**Farm labeled Fecal Dataset**	**Accuracy**	0.910	0.937	0.929	0.941	0.946	0.973
		Sensitivity	0.939	0.959	0.948	0.965	0.973	0.983
		Specificity	0.820	0.896	0.845	0.921	0.924	0.965
	Poultry Diseases Diagnostics Dataset	**Accuracy**	0.906	0.961	0.944	0.961	0.965	0.975
		Sensitivity	0.948	0.981	0.974	0.983	0.984	0.985
		Specificity	0.810	0.921	0.888	0.921	0.929	0.959

5. Conclusion

The GWO-Deep CNN model is proposed to perform efficient detection of chicken disease from the fecal image dataset. The model performs the accurate detection in the poultry chicken with decreased time consumption, which leads to a decrease death rate of the chicken in the poultry. The feature extraction process contains a structural descriptor and ResNet-101 to extract the significant region for further process. The ranking approach is involved in the feature selection to reduce the feature dimensions extracted in the image. GWO-Deep CNN minimizes the complexity, classifies the image with high accuracy, and detects healthy and sick chickens in poultry. The performance metrics such as accuracy, sensitivity, and specificity are utilized to analyze the GWO-Deep CNN that attains 0.973, 0.983, and 0.965 progressively. Furthermore, hybrid optimization can be utilized to produce the outcome of the research efficiently.

6. Future Work

A potential future direction for this research is to investigate additional Deep learning techniques or hybrid models that combine different algorithms to further enhance the accuracy of chicken diseases diagnosis. The researchers could aim to expand the dataset used for training these models by including a wider range of patient demographics, tumor characteristics, and imaging modalities. This approach could lead to the development of more robust and generalizable diagnostic models that perform effectively across diverse populations and imaging techniques.

6 Declarations

Declarations of interest: Not Applicable.
Conflict of Interest: Not Applicable
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Consent to participate: Not Applicable
Consent to publication: Not Applicable
Ethical Approval: Not Applicable.
Informed consent: None
Availability of Code/ Data/Material: Not Applicable

7 Reference

[1] Degu, M.Z. and Simegn, G.L., 2023. Smartphone-based detection and classification of poultry diseases from chicken fecal images using deep learning techniques. Smart Agricultural Technology, 4, p.100221. https://doi.org/10.1016/j.atech.2023.100221

[2] Cuan, K., Zhang, T., Huang, J., Fang, C. and Guan, Y., 2020. Detection of avian influenza-infected chickens based on a chicken sound convolutional neural network. Computers and electronics in agriculture, 178, p.105688. https://doi.org/10.1016/j.compag.2020.105688

[3] Ahmed, G., Malick, R.A.S., Akhunzada, A., Zahid, S., Sagri, M.R. and Gani, A., 2021. An approach towards IoT-based predictive service for early detection of diseases in poultry chickens. Sustainability, 13(23), p.13396. https://doi.org/10.3390/su132313396

[4] Neethirajan, S.,2022. ChickTrack–a quantitative tracking tool for measuring chicken activity. Measurement, 191, p.110819. https://doi.org/10.1016/j.measurement.2022.110819

[5] Gu, K., Song, Z., Zhou, C., Ma, P., Li, C., Lu, Q., Liao, Z., Huang, Z., Tang, Y., Li, H. and Zhao, Y., 2022. Development of a nanobody-horseradish peroxidase-based sandwich ELISA to detect Salmonella Enteritidis in milk and in vivo colonization in chicken. Journal of Nanobiotechnology, 20(1), p.167. https://doi.org/10.1186/s12951-022-01376-y

[6] Krig, S. and Krig, S., 2016. Image pre-processing. Computer Vision Metrics: Textbook Edition, pp.35-74. https://doi.org/10.1007/978-3-319-33762-3_2

[7] Renukalatha, S. and Suresh, K.V., 2017. AUTOMATIC ROI EXTRACTION IN NOISY MEDICAL IMAGES. ICTACT Journal on Image & Video Processing, 7(4). 10.21917/ijivp.2017.0215

[8] Kumar, G. and Bhatia, P.K., 2014, February. A detailed review of feature extraction in image processing systems. In 2014 Fourth International Conference on Advanced Computing & Communication Technologies (pp. 5-12). IEEE. https://doi.org/10.1109/ACCT.2014.74

[9] Biasotti, S., Marini, S., Spagnuolo, M. and Falcidieno, B., 2006. Sub-part correspondence by structural descriptors of 3D shapes. Computer-Aided Design, 38(9), pp.1002-1019. https://doi.org/10.1016/j.cad.2006.07.003

[10] Li, S., Jiao, J., Han, Y. and Weissman, T., 2016. Demystifying resnet. arXiv preprint arXiv:1611.01186. https://doi.org/10.48550/arXiv.1611.01186

[11] Elhariri, E., El-Bendary, N. and Taie, S.A., 2020. Using hybrid filter-wrapper feature selection with multi-objective improved-salp optimization for crack severity recognition. IEEE Access, 8, pp.84290-84315. https://doi.org/10.1109/ACCESS.2020.2991968

[12] Song, R., Zhang, Z., and Liu, H., 2017. Edge connection-based Canny edge detection algorithm. Pattern Recognition and Image Analysis, 27, pp.740-747. https://doi.org/10.1134/S1054661817040162

[13] Jiang, X., Hu, Y. and Li, H., 2009, July. A ranking approach to keyphrase extraction. In Proceedings of the 32nd international ACM SIGIR conference on Research and development in information retrieval (pp. 756-757). https://doi.org/10.1145/1571941.1572113

[14] Mirjalili, S., Mirjalili, S.M. and Lewis, A., 2014. Grey wolf optimizer. Advances in engineering software, 69, pp.46-61. https://doi.org/10.1016/j.advengsoft.2013.12.007

[15] Willits-Smith, A., Aranda, R., Heller, M.C. and Rose, D., 2020. Addressing the carbon footprint, healthfulness, and costs of self-selected diets in the USA: a population-based cross-sectional study. The Lancet Planetary Health, 4(3), pp.e98-e106. https://doi.org/10.1016/S2542-5196(20)30055-3

[16] Neethirajan, S., 2022. Automated tracking systems for the assessment of farmed poultry. Animals, 12(3), p.232. https://doi.org/10.3390/ani12030232

[17] Lai, S., Qin, Y., Cowling, B.J., Ren, X., Wardrop, N.A., Gilbert, M., Tsang, T.K., Wu, P., Feng, L., Jiang, H. and Peng, Z., 2016. Global epidemiology of avian influenza A

H5N1 virus infection in humans, 1997–2015: a systematic review of individual case data. The Lancet Infectious Diseases, 16(7), pp. e108-e118. https://doi.org/10.1016/S1473-3099(16)00153-5

[18] Banakar, A., Sadeghi, M. and Shushtari, A., 2016. An intelligent device for diagnosing avian diseases: Newcastle, infectious bronchitis, avian influenza. Computers and electronics in agriculture, 127, pp.744-753. https://doi.org/10.1016/j.compag.2016.08.006

[19] Kalshetty, R. and Parveen, A., 2023. Abnormal event detection model using an improved ResNet101 in a context-aware surveillance system. Cognitive Computation and Systems, 5(2), pp.153-167. https://doi.org/10.1049/ccs2.12084

[20] Zhang, Q., 2022. A novel ResNet101 model based on dense dilated convolution for image classification. SN Applied Sciences, 4, pp.1-13. https://doi.org/10.1007/s42452-021-04897-7

[21] Lin, S.L., 2021. Application combining VMD and ResNet101 in intelligent diagnosis of motor faults. Sensors, 21(18), p.6065. https://doi.org/10.3390/s21186065

[22] Satpathy, A., Jiang, X. and Eng, H.L., 2014. LBP-based edge-texture features for object recognition. IEEE Transactions on Image Processing, 23(5), pp.1953-1964. https://doi.org/10.1109/TIP.2014.2310123

[23] Sekehravani, E.A., Babulak, E. and Masoodi, M., 2020. Implementing canny edge detection algorithm for noisy images. Bulletin of Electrical Engineering and Informatics, 9(4), pp.1404-1410. DOI: 10.11591/eei.v9i4.1837

[24] Mbelwa, H., Machuve, D. and Mbelwa, J., 2021. Deep convolutional neural network for chicken disease detection. https://dx.doi.org/10.14569/IJACSA.2021.0120295

[25] Kumar, S., Singh, S.K., Singh, R.S., Singh, A.K. and Tiwari, S., 2017. Real-time recognition of cattle using animal biometrics. Journal of Real-Time Image Processing, 13, pp.505-526. https://doi.org/10.1007/s11554-016-0645-4

[26] Suthaharan, S. and Suthaharan, S., 2016. Support vector machine. Machine learning models and algorithms for big data classification: thinking with examples for effective learning, pp.207-235. https://doi.org/10.1007/978-1-4899-7641-3_9

[27] Li, G., Hui, X., Lin, F. and Zhao, Y., 2020. Developing and evaluating poultry preening behavior detectors via mask region-based convolutional neural network. Animals, 10(10), p.1762. https://doi.org/10.3390/ani10101762

[28] Guo, Y., Aggrey, S.E., Wang, P., Oladeinde, A. and Chai, L., 2022. Monitoring behaviors of broiler chickens at different ages with deep learning. Animals, 12(23), p.3390. https://doi.org/10.3390/ani12233390

[29] Mbelwa, H., 2021. Image-based poultry disease detection using deep convolutional neural network (Doctoral dissertation, NM-AIST). https://doi.org/10.58694/20.500.12479/1344

[30] Tixier-Boichard, M., Bed'Hom, B. and Rognon, X., 2011. Chicken domestication: from archeology to genomics. Comptes Rendus. Biologies, 334(3), pp.197-204. https://doi.org/10.1016/j.crvi.2010.12.012

[31] Huang, J., Wang, W. and Zhang, T., 2019. Method for detecting avian influenza disease of chickens based on sound analysis. Biosystems Engineering, 180, pp.16-24. https://doi.org/10.1016/j.biosystemseng.2019.01.015

[32] Poultry Disease Diagnostics https://www.kaggle.com/datasets/kausthubkannan/poultry-diseases-detection, accessed on April 2024.

[33] Farm labeled fecal images https://data.mendeley.com/datasets/8pnbzpt2k9/1, accessed on April 2024.

[34] Vandana, Yogi, K. K., Yadav, S.P., 2024. Chicken Diseases Detection and Classification Based on Fecal Images Using EfficientNetB7 Model. EVERGREEN Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy, Vol. 11, Issue 01. https://doi.org/10.5109/7172288.

[35] Vandana, K. Kumar Yogi and Yadav, S. P., 2023, Surveillance to Detect and Classifying of Chicken Poultry Diseases from Fecal Images Using CNN. 2023 6th International Conference on Contemporary Computing and Informatics (IC3I), Gautam Buddha Nagar, India, pp. 939-943, https://doi.org/10.1109/IC3I59117.2023.10397876.

[36] Naik, N. K., Sethy, P. K., Devi, A. G., & Behera, S. K. 2024. Few-shot learning convolutional neural network for primitive indian paddy grain identification using 2D-DWT injection and grey wolf optimizer algorithm. Journal of Agriculture and Food Research, 15, 100929. https://doi.org/10.1016/j.jafr.2023.100929

[37] Abuya, T. K., Waithera, W. C., & Kipruto, C. W., 2024. Augmented lung cancer prediction: Leveraging convolutional neural networks and Grey Wolf Optimization algorithm. *OALib*, *11*(04), pp. 1–25. https://doi.org/10.4236/oalib.1111172

[38] Liu, L., Zhang, X., & Xu, Z., 2024. An adaptive weight search method based on the Grey wolf optimizer algorithm for skin lesion ensemble classification. International Journal of Imaging Systems and Technology, *34*(2). https://doi.org/10.1002/ima.23049

[39] Sharma, D. K., Singh, P., & Punhani, A., 2024. Sugarcane Diseases Detection using the Improved Grey Wolf Optimization Algorithm with Convolution Neural Network. International Journal of Experimental Research and Review, *38*, pp. 246–254. https://doi.org/10.52756/ijerr.2024.v38.022

[40] Sharmila, V., & Ezhumalai, P., 2024. Diagnosis of skin lesion using shift-invariant network and an improved grey wolf optimizer. Journal of Intelligent & Fuzzy Systems, 46(3), pp.5635–5653. https://doi.org/10.3233/jifs-232325

[41] Seetha, J., Ramanathan, R., Goyal, V., Tholkapiyan, M., Karthikeyan, C., & Kumar, R., 2023. Mango leaf disease classification using hybrid Coyote-Grey Wolf optimization tuned neural network model. Multimedia Tools and Applications, 83(6), 17699–17725. https://doi.org/10.1007/s11042-023-16964-9

[42] Bilal, A., Sun, G., Mazhar, S., & Imran, A., 2022. Improved Grey Wolf Optimization-Based feature selection and classification using CNN for diabetic retinopathy detection. In Lecture notes on data engineering and communications technologies (pp. 1–14). https://doi.org/10.1007/978-981-16-9605-3_1

[43] Gopatoti, A., & Vijayalakshmi, P., 2022. CXGNet: A tri-phase chest X-ray image classification for COVID-19 diagnosis using deep CNN with enhanced grey-wolf

optimizer. *Biomedical Signal Processing and Control*, *77*, 103860. https://doi.org/10.1016/j.bspc.2022.103860

[44] Gülmez, B., 2023. A novel deep learning model with the Grey Wolf Optimization algorithm for cotton disease detection. JUCS - Journal of Universal Computer Science, *29*(6), pp.595–626. https://doi.org/10.3897/jucs.94183

[45] Sallam, N. M., Saleh, A. I., Ali, H. A., & Abdelsalam, M. M., 2022. An efficient strategy for blood diseases detection based on grey wolf optimization as feature selection and machine learning techniques. *Applied Sciences*, *12*(21), 10760. https://doi.org/10.3390/app122110760

[46] Mohakud, R., & Dash, R., 2022. Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection. Journal of King Saud University - Computer and Information Sciences, 34(8), pp.6280–6291. https://doi.org/10.1016/j.jksuci.2021.05.012