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Intelligent Diagnosis of Adverse Agrochemical Effects on Chemical & Farm Workers

P Yugandhar Reddy, P Koteswara Rao

Dept. of CSE

Acharya Nagarjuna University, Guntur.

Ch Divya, N Abhinav, G Jeevankumar

Dept. of CSE

Acharya Nagarjuna University, Guntur.

ABSTRACT

Since World War II (1939–1945), the use of synthetic fertilizers and pesticides, collectively known as agrochemicals, has grown significantly to avoid pests, reduce agricultural losses, and enhance food quality and yields. However, exposure to these agrochemicals poses substantial health risks to farmers and chemical workers. Researchers found that this exposure may be linked to many serious health issues including Cancers, Neurological disorders, skin problems, respiratory diseases, etc. Despite the critical importance of addressing these health risks due to the lack of awareness and symptoms being unreported , diagnosing diseases caused by agrochemical exposure remains . Overcoming these challenges requires a multi-faceted approach. Our research project focuses on early diagnosis of diseases through intelligent diagnostic tools based on specific symptoms. Early detection can enable timely medical attention, potentially preventing serious health complications.By leveraging the power of AI and ML, our study performs two main tasks: multiclass classification on numerical data using the XGBoost classifier and binary image classification using a CNN Sequential_5 model. The XGBoost classifier has proven to be highly effective for multiclass classification tasks on numerical data, achieving near-perfect accuracy and consistency.The CNN model demonstrates high reliability and generalization capability in binary image classification, effectively distinguishing between the two main diseases caused by exposure namely Contact Dermatitis and Skin Cancer. The successful use of these diagnostic models has far-reaching implications in healthcare, policy-making in chemical and agricultural workplaces. This research also helps in promoting the preventive measures and creating the awareness among people about the adverse effects of using agrochemicals.

Key Words: Agrochemical Toxicity, Occupational Exposure, Skin Cancers, Contact Dermatitis, Respiratory Problems, Disease Diagnosis, Predictive Models, Preventive Measures, Improving Awareness.

I. Introduction:

Background: At present, more than 40% of today's global population works in agriculture, making it the single largest employer in the world. Also, about 58% of the Indian population depends on agriculture for their livelihood. The methods of farming have been completely changed and modernized in such a way that people stopped using traditional farming techniques and traditionally made organic crop yield enhancers made out of biodegradable waste and many more. Since World War 11 (1939–1945), the use of synthetic fertilizers and pesticides, collectively known as agrochemicals, has grown significantly to avoid, eliminate, or eradicate pests, lower losses in agricultural production, and enhance food quality and cheap yields. The main drivers of the increase in pesticide use in farming are population expansion and food demand, technological developments, and time and financial incentives. At present, India is the fourth largest producer of pesticides in the world after the U.S., Japan, and China, and ranks 12th in pesticide use globally with annual production of 90,000 tons. The use of pesticides and fertilizers is integral to modern agricultural practices, significantly enhancing crop yields and ensuring global food security.

Understanding Research Problem Statement: However, exposure to these pesticides and fertilizers both environmental and occupational exposure poses substantial health risks to farmers and chemical workers, who are often on the frontline of handling these substances. Both direct and indirect environmental/occupational exposure of humans to agrochemicals may result in both acute and chronic health diseases if ignored for a long time. Farmers and chemical workers can be exposed to agrochemicals in many ways including dermal absorption, inhalation, Ingestion, etc. This exposure may be linked to many serious health issues including Cancers, Neurological disorders, skin problems, respiratory diseases, etc. Despite the crucial importance of addressing these health risks, diagnosing these diseases caused by agrochemical exposure remains challenging due to the non-specific nature of symptoms, varied exposure levels, underreporting, and a general lack of awareness among workers about the potential dangers linked to the exposure to agrochemicals and necessary safety measures that must be taken while using them.

Overview: So, overcoming these challenges is very important and it also requires a multi-faceted approach. Our research project mainly focuses on raising awareness among people and early diagnosis of the disease by developing intelligent diagnostic tools based on the type of symptoms we are dealing with. This research project, aims to tackle these challenges by leveraging powerful and promising approaches of machine learning (ML) and deep learning (DL) techniques. By collecting and analyzing data on symptoms and other useful parameters like age, and gender reported by individuals exposed to pesticides and fertilizers, we developed a predictive model capable of diagnosing potential diseases early. Their ability to analyze complex data, predict early warning signs, provide personalized risk assessments, and continuously learn and improve makes them valuable tools in protecting the health of agricultural workers and communities.

Significance and Contributions:

Our project introduces a novel approach to early diagnosis of agrochemical-related diseases. By leveraging ML and DL, our research offers a more accessible and potentially cost-effective tool compared to traditional methods. This not only facilitates timely medical intervention but also underscores the importance of preventive measures and safety practices in agricultural and chemical industries. Also empowers farmers and chemical workers with knowledge about their health conditions and risks. Early detection through this model can enable them to seek timely medical attention, potentially preventing serious health complications. Our research also mainly focuses on promoting preventive measures and safety precautions that must be taken while handling pesticides and fertilizers. This could lead to increased adoption of protective measures, reducing exposure and the associated health risks. Not but not least, Advancing AI in Agricultural Health.

Structure : The format of this document is as follows: A thorough methodology of our data collecting and model training procedures is given in the next section. We collect data by asking afflicted persons about their symptoms in great detail. We then use this information to develop pre-trained machine learning and deep learning models that use model selection and model-building algorithms to forecast potential diseases. Finally, we show our findings and talk about their consequences. The goals of this program are to increase agrochemical safety knowledge, promote better health outcomes for farm and chemical workers, and improve early diagnosis. This project's successful completion shows how cutting-edge technology, such as artificial intelligence (AI), may revolutionize agricultural health monitoring and shield vulnerable communities from the harmful impacts of necessary but dangerous agricultural inputs.

Related Work: Numerous studies have documented the adverse health effects of agrochemical exposure on farmers as well as chemical workers working in agrochemical industries and retail shops. Main research areas related to our project which have been covered in the past include:

1.Exposure of chemical workers & Farmers to agrochemicals

The relationship between extent of pesticide use and signs and symptoms of illnesses due to exposure was confirmed in a cross-sectional survey of 631 farmers (537 men and 94 women) in South India[1].Exposure often occurs via dermal and inhalation routes, with uncovered areas like the face and hands being the most vulnerable[7].The study states that there's a serious risk of work-related health issues due to the frequent use of agrochemicals and the lack of training and safety measures in place[6]. Shopkeepers who sell pesticides are regularly exposed to various types of pesticides, including organophosphates, organochlorines, carbamates, and pyrethroids [3].

2.Disesases caused due to exposure to pesticides.

There is a significant association between the use of certain pesticides (maneb/mancozeb, parathion, and carbaryl) and an increased risk of developing melanoma[2]. Due to the exposure to manures, fertilizers, pesticides, and prolonged sunlight, these workers are at risk for various skin diseases including both infectious and non-infectious ones[9]. Common skin conditions include contact dermatitis (allergic and irritant), with rarer forms such as urticaria and chloracne[10].

3.Precautions and Preventive measures

To minimize these risks, it is crucial to reduce pesticide use and ensure the proper use of personal protective equipment at all stages of pesticide handling[4]. Addressing these hazards requires effective regulations, proper training, and education to promote safer, sustainable agricultural practices and mitigate the negative impacts of pesticide use[11].

4.Use of AI, ML and DL in Disease Prediction

Machine Learning (ML) is being used to help in the early identification of numerous diseases[13]. ML and AI methodologies are commonly employed in disease prediction, including supervised and unsupervised learning algorithms, deep learning techniques, and ensemble methods[14].

Gaps Identified and Recommended Approach

It is evident that exposure to pesticides and fertilizers both environmentally and occupationally may result in infectious & non-infectious skin diseases and dangerous skin cancers like Melanoma. It is also understood that proper care and preventive measures should be taken beforehand while dealing with pesticides and fertilizers. Though AI & its subfields are the best choice for early disease prediction, the data on which the model is working is more generalized and irrelevant to the context of symptoms caused by using pesticides and fertilizers.

So in our project, we use the data on symptoms that is more specific to the research. That is, we only focus on the diseases and symptoms that may occur due to exposure to agrochemicals. We then build and train our ML model on this domain-specific data and predict the respective disease which they might be suffering with.

II. Materials and Methods

This study is an observational, cross-sectional study designed to investigate the health impacts of agrochemical exposure among agricultural and chemical workers. Data were collected at a single point in time from farmers and chemical workers to analyze the prevalence and types of health symptoms associated with pesticide and fertilizer exposure.

1.Data Preparation

1) In our research project, we mainly focus on taking data from the selected population in two different formats from different population and training them using two different classifiers:
2) Multiclassification using numerical data –
    - 0-if not suffering from the respective symptom
    - 1-if actually suffering from that symptom
3) Binary classification using Skin Image data
    - Taking the image of the part of the skin which is affected.

We process these two formats using two different approaches.

2.Data Collection

a) Collecting numerical data for multi-classification

We have chosen a labeled data set that contains a population of 4961 observations as rows correspond to individual observations or persons and 132 columns having 131 symptoms and the last column as the output column named "prognosis". The symptoms we have considered are "[itching, skin_rash, nodal_skin_eruptions, ulcers_on_tongue, redness_of_eyes, blackheads,scurring…….irritability, toxic_look_(typos), depression, yellowish_skin, loss_of_smell, irritation_in_anus]"
The respective data entries would be 0 or 1.

1. 0-if not suffering from symptom
2. 1-if actually suffering from that symptom

We also collect extra information from users like, name, age, gender, profession working perod, etc. to support our predictions made for the given symptom.

b) Collecting skin image data for binary classification

As we are doing binary classification we have collected images belonging to two main classes namely "Contact Dermatitis & Skin cancer". We stored them in two different folders each containing around 1900 images. We have collected images of contact dermatitis from web sources . We have filtered out "Basal cell carcinoma, squamous cell carcinoma, and melanoma" skin cancer images from popular "HAM10000 data set" which are the most common forms of skin cancer.

3.Data Preprocessing

Data Cleaning: We conducted a thorough inspection to identify any null (missing) values within the dataset. This involved scanning each column and row to ensure data completeness. Upon identifying columns with null values, we proceeded to drop the column "Unnamed" from the dataset as an empty column with null values. We also removed all the unwanted and redundant images from the image folders.

Data Augmentation: For numerical data: In our numerical labeled dataset, we manually transformed the symptom columns based on their similarity to facilitate easier input by users. Related symptoms were placed side by side, making it simpler for users to find and enter symptoms without having to search through the entire list. Additionally, we performed label encoding on the categorical variable "prognosis," which represents the output. This process resulted in labels ranging from 0 to 40, each representing a distinct disease category.

For our image-labeled dataset, we first reduced the size of all images to 100x100 pixels to meet memory requirements. Next, we converted all RGB images into numeric arrays and normalized these array values to a range of 0 to 1. Additionally, we converted the binary classes into labels: 0 for Contact Dermatitis and 1 for Skin Cancer as shown in fig. 1 below.

Data Splitting: For the numerical labeled dataset, we used the "train_test_split" function to divide the data into distinct training (80%) and testing(20%) datasets to evaluate model performance and for image data, we split the data into three parts namely train(60%),validate(20%) and test(20%) data sets .

4. Model building, training and validation

Model Selection: For the task of multiclassification on numerical data, We chose XGBoost data due to its superior performance, regularization, missing data handling, and efficiency. By leveraging XGBoost, we aim to build a robust and accurate model that can effectively classify our numerical data into multiple categories.

We chose a Convolutional Neural Network (CNN) for binary classification of our image dataset due to its ability to learn features from high-dimensional image data and its proven success in image classification tasks. This ensures high accuracy and reliability in our task.

Fig. 1: Plot showing preprocessed image data

Model Architecture:

A) Architecture of XG Boost classifier:

1.Input: Numeric features

2.Decision Trees (Multiple): Each tree splits the data based on different features and makes predictions.

3.Gradient Boosting: The model is optimized iteratively using gradients to correct errors.

4.Regularization: L1 and L2 regularization are applied to prevent overfitting.
5.Loss Function: Measures the difference between predictions and actual values.
6.Output: Probabilities for each class (multiclass classification) or a single probability (binary classification) as shown in fig.2 below.

B) Overall Structure of CNN (Sequential_5):

The model is designed for image classification and follows a typical CNN structure with alternating convolutional and pooling layers, followed by fully connected layers for classification.

Layer Details:

1.Input Layer (Implicit):

- The model expects input images of size 100 x 100 pixels (this isn't explicitly stated in the summary, but can be inferred from the output shape of the first layer).
- The number of channels (colors) isn't specified, but is likely 3 for RGB images.

2.Convolutional Layer (conv2d_15):

- **Filters:** 32 filters (also called kernels)
- **Kernel Size:** 3x3
- **Activation:** Likely ReLU (Rectified Linear Unit), though not explicitly mentioned.
- **Output Shape:** (None, 98, 98, 32)
  - None represents the batch size (number of images processed at once).
  - 98x98 is the spatial dimension of the feature maps after the convolution.
  - 32 is the number of channels (feature maps) produced by the 32 filters.

3.Max Pooling Layer (max_pooling2d_15):

- **Pool Size:** 2x2
- **Stride:** 2 (moves the pooling window by 2 pixels in each direction)
- **Output Shape:** (None, 49, 49, 32)

- The spatial dimensions are halved due to the pooling operation.

4.Convolutional Layer (`conv2d_16`):

- **Filters:** 64
- **Kernel Size:** 3x3
- **Activation:** Likely ReLU
- **Output Shape:** (None, 47, 47, 64)

5.Max Pooling Layer (`max_pooling2d_16`):

- **Pool Size:** 2x2
- **Stride:** 2
- **Output Shape:** (None, 23, 23, 64)

6.Convolutional Layer (`conv2d_17`):

- **Filters:** 128
- **Kernel Size:** 3x3
- **Activation:** Likely ReLU
- **Output Shape:** (None, 21, 21, 128)

7.Max Pooling Layer (`max_pooling2d_17`):

- **Pool Size:** 2x2
- **Stride:** 2
- **Output Shape:** (None, 10, 10, 128)

8.Flatten Layer (`flatten_5`):

- Transforms the 3D feature maps into a 1D vector to prepare for fully connected layers.
- **Output Shape:** (None, 12800)

9.Dense Layers (`dense_20`, `dense_21`, `dense_22`):

- **Units:** 512, 256, 128 respectively
- **Activation:** Likely ReLU
- Progressively reduce the number of neurons to refine the learned features.

10.Output Layer (`dense_23`):

- **Units:** 1
- **Activation:** None or linear as shown in fig.3 below.

Key Concepts:

- **Feature Extraction:** The initial convolutional and pooling layers extract hierarchical features from the images.
- **Classification:** The fully connected layers combine and interpret the extracted features to make the final binary classification decision.
- **Regularization:** Not explicitly mentioned in the summary, but techniques like dropout or L1/L2 regularization could be used to prevent overfitting.

Model Training and hyper parameter tuning

We trained our XGBoost Classifier on the training data using the best parameters obtained upon performing the Hyper Parameter Tuning using "GridSearch CV".The best values obtained for each parameter are as

Parameter	Tested Values	Best Value
learning_rate max_depth n_estimators	0.1, 0.2 3, 5 100, 200	0.1 3 100
Best score		0.999496094

follows:

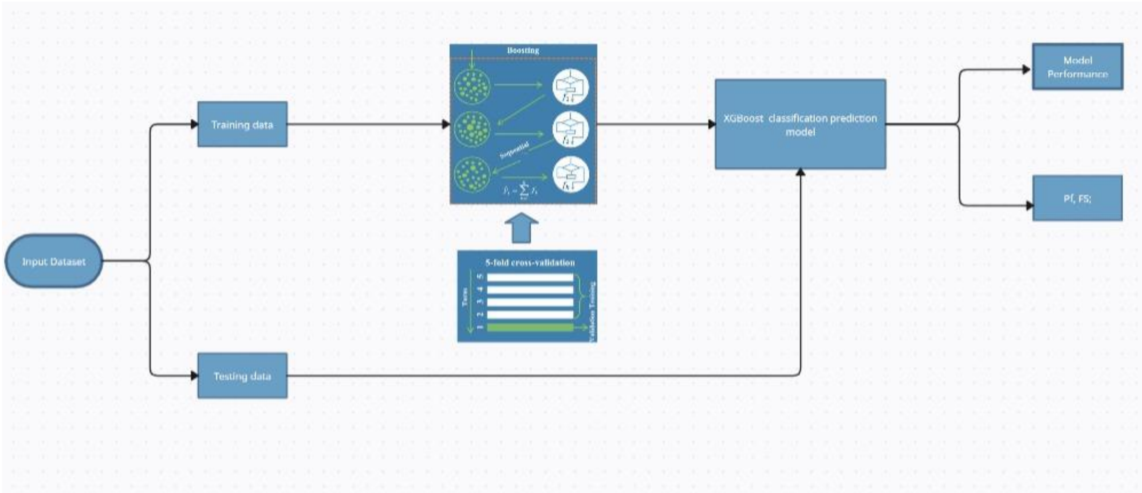

Fig. 2: Architecture of XGBoost Classifier

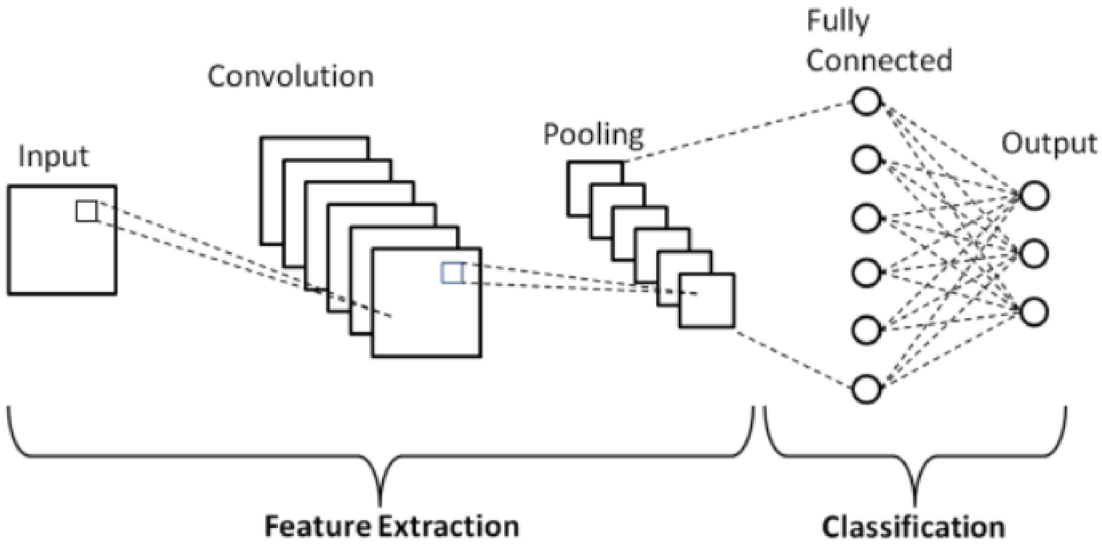

Fig. 3: Architecture of CNN Sequential_5

For binary image classification, we train the CNN “sequential_5” model using training data and validate using the validation data set.

Model Validation and evaluation:

We performed K-fold cross-validation on both the XGBoost classifier and the Sequential_5 model of the Convolutional Neural Network (CNN), using 5 folds (k=5) for the entire dataset. This approach ensured robust validation by training and validating the models on different subsets of the data and the results are stored in the below mentioned table for XGBoost classifier and cross matrices for each fold for sequential_5 model.

To evaluate the models' performance, we used several metrics and tools like

1) **Classification report** for providing detailed insights into accuracy,precision, recall, F1-score, and support for each class.

2)**Confusion Matrix** to offer a comprehensive view of the true positive, true negative, false positive, and false negative predictions.

3) **Training vs. Validation Metrics** used to plot the graphs for training accuracy vs.

validation accuracy and training loss vs. validation loss to visualize and compare the learning progress and performance of the models.
This comprehensive evaluation allowed us to assess the effectiveness and reliability of both models in our classification tasks.
We have also extracted the Feature importance from the trained XGBoost model xgb_model.feature_importances_, helping you understand which features contribute the most to the model's predictions.

III. Results and Discussions

1.XGBoost Classifier

1.1Validation Results

On performing the K-Fold Cross-Validation on the XGBoost Classifier for k=5 The model achieved an accuracy of 1.0 for four folds and an accuracy of 0.998 for the second fold. This indicates a highly consistent performance across different subsets of the data, with only a marginal deviation in one fold as shown:

CV_Folds	CV_Scores
Fold1	1.
Fold2	0.99899
Fold3	1.
Fold4	1.
Fold5	1.
Mean CV accuray	**0.99979**
Standard deviation of CV accuracy	**0.00040**

Table 1:CV Results of XG Boost

The classification report represents the precision, recall, F1-Score nearly equal to 1. These metrics confirm that the model is highly reliable in predicting the correct classes without any false positives or false negatives.

	Precision	Recall	F1-score
0-40 classes	1.00	1.00	1.00
Accuracy			1.00
Macro avg	1.00	1.00	1.00
Weighted avg	1.00	1.00	1.00

Table 2: Classification Report for XGBoost

The confusion matrix further supports the model's robustness, with all non-diagonal values being zero. This means that all predictions made by the model are correct, placing the predicted classes exactly where they belong.

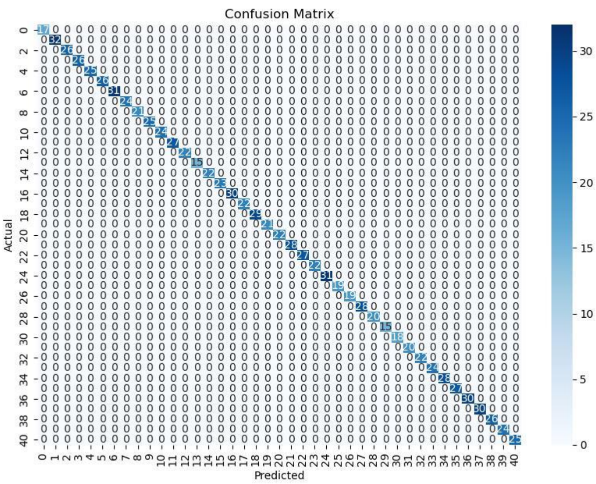

Fig.4:Final Confusion Matrix for XGBoost

The graph showing feature importances

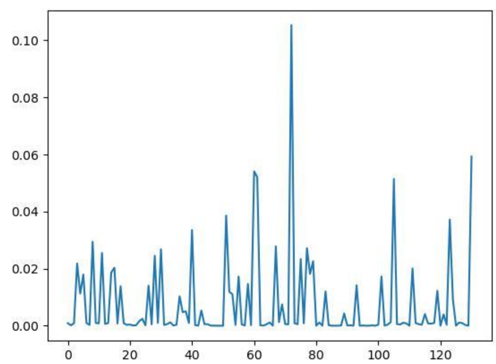

Fig.5:Plot to show the feature importances

The feature importances are shown in discending order of their importance as shown in below table

Index	Feature	Importance
72	Movement_stiffness	0.105352
130	Irritation_in_anus	0.059304
60	Prominent_veins_on_calf	0.054089
…	…..	…
86	anxiety	0.000000
85	Weight_gain	0.000000
48	Sinus_pressure	0.000000

Table 3:Features and their Importances

1.2Performance Visualizations

The training vs. validation accuracy and loss graphs shpown in fig. are ideal, showing no signs of overfitting or underfitting . Both training and validation metrics converge smoothly, indicating that the model generalizes well to unseen data.

The XGBoost classifier has proven to be an outstanding choice for the given multiclass classification task on numerical data. Its high accuracy, perfect classification metrics, and excellent generalization capabilities underscore its effectiveness and reliability. This makes it a strong candidate for practical implementations and further applications in similar domains. Additionally, continuous monitoring and evaluation in a production environment are necessary to ensure sustained performance.

2. CNN Model (Sequential_5)

2.1Validation Results

The CNN model (Sequential_5) was validated using 5-fold cross-validation, yielding the following validation accuracies for each fold: [0.9585, 0.9563, 0.9694, 0.9105, 0.9563]. This indicates a high level of consistency and robustness across different subsets of the data, with only a slight drop in one fold (0.9105), which might be attributed to variability in the data distribution for that specific fold.

The confusion matrices shown below for each fold as shown confirmed that the model was able to accurately classify the binary outcomes (Contact Dermatitis vs. Skin Cancer) with minimal misclassifications.

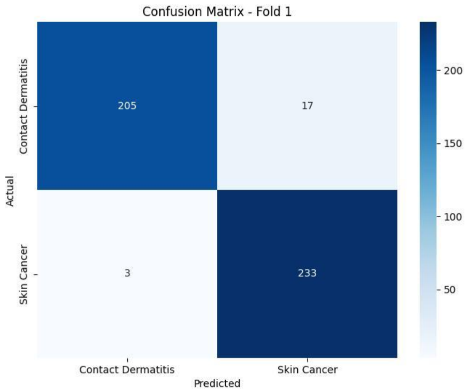

Fig.6.1: Confusion Matrix-Fold 1

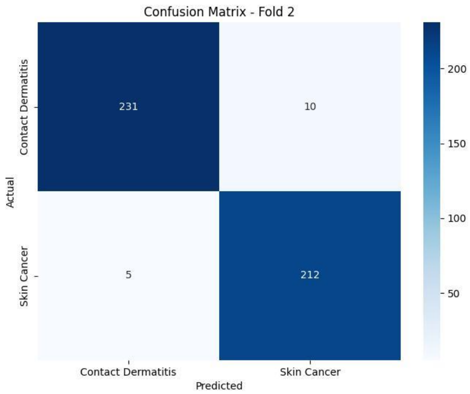

Fig.6.2: Confusion Matrix-Fold 2

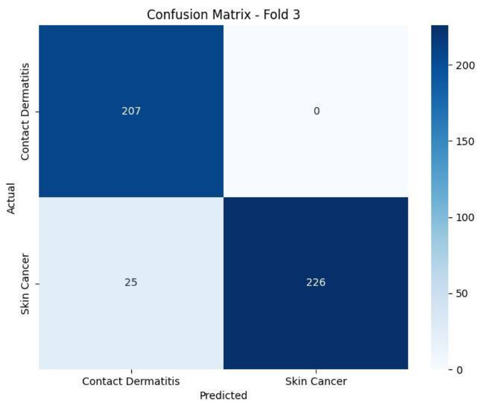

Fig.6.3: Confusion Matrix-Fold 3

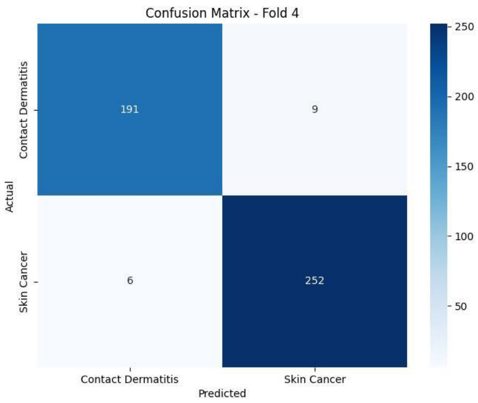

Fig.6.4: Confusion Matrix-Fold 4

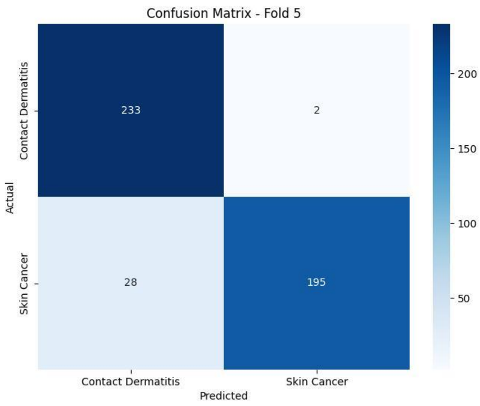

Fig.6.5: Confusion Matrix-Fold 5

The plots of training accuracies vs. validation accuracies and training losses vs. validation losses for the cross-validation shown in fig.9 showed an intersection after 10 epochs. This indicates an increase in validation accuracy corresponding with an increase in training accuracy, and a decrease in validation loss corresponding with a decrease in training loss. Such behavior is indicative of the model's ability to generalize well without overfitting.

Following the cross-validation, the model was trained on the training data (60%) and validated on the validation data (20%). The model was then evaluated on the test data (20%), resulting in:

- **Test Loss**: 0.1310
- **Test Accuracy**: 0.9620

These results demonstrate that the model performs exceptionally well on unseen test data, indicating strong generalization capabilities.

The classification report revealed that the model achieved precision, recall, F1-score, and accuracy all at 0.97. These high values across all metrics suggest that the model is very effective in distinguishing between the two classes with a balanced performance in terms of precision (correctness of positive predictions), recall (completeness of positive predictions), and the harmonic mean of both (F1-score).

	Precision	Recall	F1-score	Support
Contact dermatitis	0.97	0.97	0.97	759
Skin Cancer	0.97	0.97	0.97	769
Accuracy			0.97	1528
Macro avg	0.97	0.97	0.97	1528
Weighted avg	0.97	0.97	0.97	1528

Table 4: Classification Report for CNN Sequential_5 model

The overall final confusion matrix for the validated model further confirmed the model's strong performance, with very few misclassifications, ensuring high reliability and accuracy in real-world scenarios.

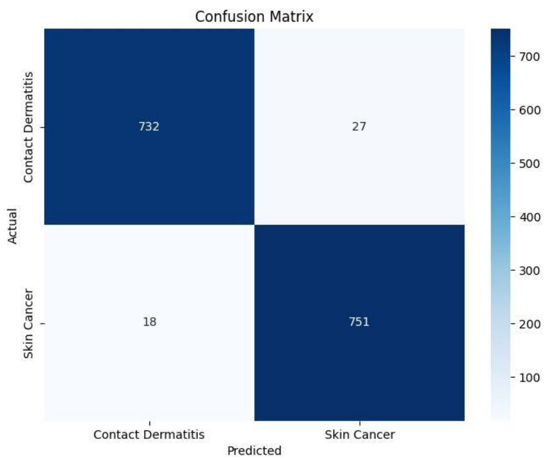

Fig.7: Final Confusion Matrix

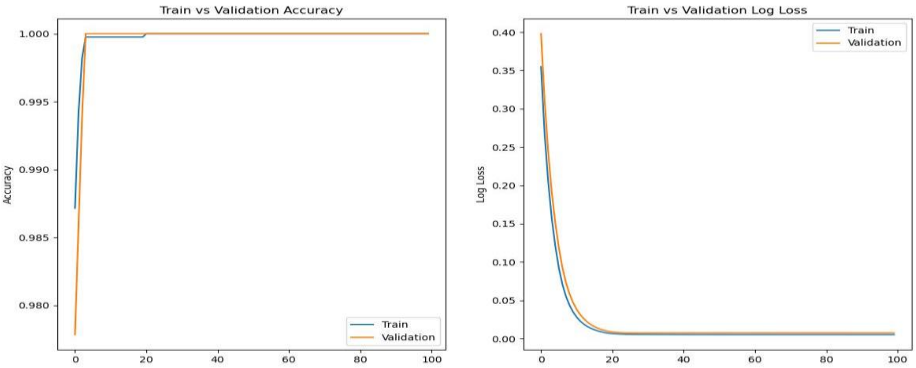

Fig.8: The training vs. validation accuracy and loss graphs

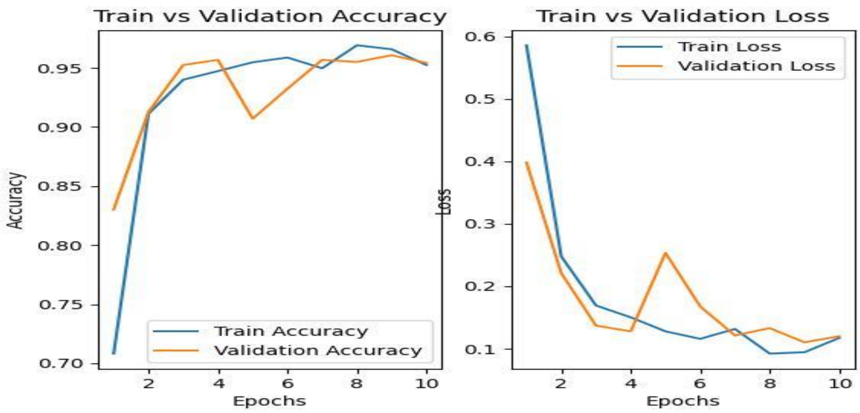

Fig.9: The plots of training vs validation accuracies and losses for the cross-validation

The final plots of training accuracies vs. validation accuracies and training losses vs. validation losses are shown in fig 10 below were similar to those observed during cross-validation. The consistency in these plots underscores the model's stability and effectiveness across different training and validation phases.

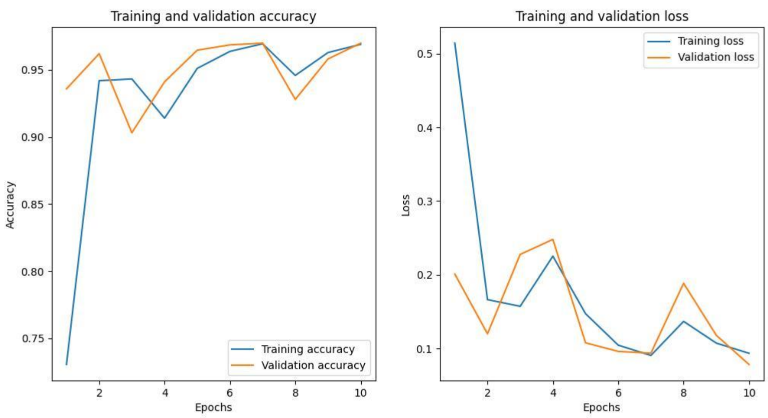

Fig.9: The plots of training vs validation accuracies and losses for the cross-validation

The CNN model demonstrates high reliability and generalization capability in binary image classification tasks, as evidenced by consistently high accuracy across validation and test data. Its balanced performance in identifying both classes, along with effective feature learning, makes it suitable for practical applications such as medical diagnostics. Further research could explore data augmentation and broader dataset testing for enhanced applicability. Continuous monitoring in a production environment is also recommended to maintain the model's performance over time.

Conclusion

Our research project was initiated to address the critical issue of accurately diagnosing the health impacts of agrochemicals on workers in the agricultural sector. The primary objective was to develop an intelligent diagnostic system capable of identifying adverse effects caused by exposure to these chemicals, leveraging both numerical data on symptoms and image data for accurate classification.

Objective and Achievements: Our objective was to create a robust and reliable diagnostic tool that could assist in early detection and prevention of agrochemical-related health issues among farm workers. Through this study, we successfully developed and validated two distinct models namely A XGBoost classifier for multiclass classification of numerical symptom data and A Convolutional Neural Network (CNN) for binary classification of image data.

Key Findings: Our key findings are summarized as follows:

- **XGBoost Classifier**: The model achieved near-perfect accuracy during cross-validation and testing, demonstrating its ability to reliably classify various health conditions based on symptom data.
- **CNN Model**: The CNN achieved high precision, recall, and F1-scores, effectively distinguishing between Contact Dermatitis and Skin Cancer in image data. The model's performance metrics were consistent across multiple validation techniques, indicating strong generalization capabilities.

This research makes significant contributions to the field of occupational health and safety by providing a novel approach to diagnosing health issues using a combination of symptom-based numerical data and image data, Creating awareness among people about the adverse effects of using pesticides and fertilizers, Demonstrating the effectiveness of advanced machine learning models in medical diagnosis.

The successful implementation of these models has significant implications in healthcare to quickly and accurately diagnose health issues caused by agrochemical exposure, leading to timely and appropriate medical interventions and policy making to inform regulatory bodies about the health impacts of agrochemicals, potentially influencing policies related to the use and regulation of these chemicals in agriculture. Employers in the agricultural sector can use this tool to monitor the health of their workers, ensuring safer working conditions and reducing the risk of long-term health problems.

Recommendations: Further research could explore data augmentation and broader dataset testing for enhanced applicability. Collaboration with experts in toxicology, occupational health, and machine learning can lead to more comprehensive solutions and improvements in diagnostic accuracy. Implementing and testing the models in real-world settings will provide valuable insights into their practical utility and effectiveness.

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