CROP DISEASE CLASSIFICATION WITH RESET34, FEATURES EXTRACTION AND CNN ML MODEL

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Abstract

"E-Kissan" presents a pioneering approach to address the critical challenge of crop disease detection by seamlessly integrating Convolutional Neural Networks (CNN) and ResNet architecture. With the escalating prevalence of crop diseases threatening global food security, there is an urgent need for advanced and precise detection methods to mitigate yield losses. Conventional manual inspection methods are burdened by laborious processes, highlighting the necessity for automated solutions. In response, "E-Kissan" advocates for an innovative automated solution harnessing deep learning to accurately identify crop diseases from field-captured images. By leveraging CNN and ResNet34 models, "E-Kissan" equips farmers and agricultural stakeholders with a reliable tool for efficient disease diagnosis. At the heart of "E-Kissan" lies its commitment to simplicity and accessibility. The integration of a user-friendly React web interface streamlines the process of uploading images of affected crops and swiftly obtaining disease diagnosis. Through this intuitive platform, "E-Kissan" democratizes access to advanced disease detection technology, empowering farmers to make informed decisions and take timely actions to safeguard their crops. By revolutionizing crop disease management, "E-Kissan" represents a significant leap towards enhancing global agricultural sustainability. Its automated approach promises to revolutionize traditional methods, reducing yield losses, and bolstering the resilience of agricultural systems worldwide.

Keywords: Machine Learning Model, Convolutional Neural Networks (CNN), ResNet34.

I. INTRODUCTION

The agricultural sector is undergoing rapid transformation, leveraging modern technologies to tackle various challenges, particularly in crop disease management. Conventional methods often fall short in terms of efficiency and accuracy, driving researchers to explore innovative solutions. Mehmood et al. (2018) demonstrated the potential of deep learning techniques in disease diagnosis, showcasing their ability to automate detection processes with exceptional precision. This pivotal study laid the foundation for integrating artificial intelligence (AI) into agricultural practices, paving the way for more advanced solutions. In a seminal contribution, Mohanty et al. (2016) introduced "PlantVillage," an influential initiative aimed at revolutionizing plant disease detection and management. Through the utilization of deep learning and transfer learning algorithms, PlantVillage achieved remarkable accuracy in classifying plant diseases, offering a scalable solution for farmers worldwide. This landmark project underscored the transformative power of technology in addressing critical agricultural issues.

However, accessibility remained a significant challenge for many farmers, particularly those in remote areas with limited resources. The emergence of web-based frameworks like React.js introduced a new dimension to agricultural technology by facilitating the development of user-friendly interfaces. React.js, renowned for its versatility and simplicity, revolutionized web development, enabling developers to create interactive and intuitive applications more efficiently. With the advent of React.js, projects such as "e Kissan" have harnessed this technology to redefine crop disease prediction and management. By establishing a user-friendly website powered by React.js, "e Kissan" provides farmers with a seamless platform to upload crop images and receive accurate disease predictions in real-time. This approach enhances accessibility and usability, empowering farmers to make informed decisions regarding crop health and management practices.

The integration of React.js in "e Kissan" represents a significant advancement in agricultural technology, bridging the gap between cutting-edge AI algorithms and end-users. By prioritizing user experience and accessibility, "e Kissan" exemplifies the potential of technology to democratize access to crucial agricultural insights, ultimately contributing to improved crop yields and food security. As the agricultural sector continues its digital transformation journey, solutions like "e Kissan" are poised to play a pivotal role in shaping the future of farming.

II. LITERATURE SURVEY

Crop diseases pose a significant threat to global food security. Early and accurate detection is crucial for implementing appropriate control measures and minimizing yield losses. This survey explores a research approach that utilizes deep learning for automatic crop disease classification. The method leverages a pre-trained convolutional neural network (CNN), ResNet-34, for feature extraction and trains a separate CNN model for disease classification [4].

Plant Disease Detection Techniques: Traditional methods for crop disease detection often rely on visual inspection by experts, which can be time-consuming, subjective, and prone to errors. Deep Learning for Crop Disease Classification: Deep learning, particularly CNNs, has emerged as a powerful tool for image recognition and classification tasks. CNNs excel at extracting relevant features from images, making them well-suited for analyzing crop images for disease identification [1, 2]

Pre-trained CNNs for Feature Extraction: Pre-trained models like VGG16 and ResNet architectures have shown success in extracting informative features from plant images for disease classification tasks [3]. These models, trained on vast image datasets, learn generic features that can be beneficial for various image recognition problems, including crop disease detection[7].

CNN-based Crop Disease Classification: Numerous studies have explored using CNNs directly for crop disease classification. These studies often involve training a CNN model from scratch on labeled crop image datasets [4].

Leveraging Pre-trained Features: By employing a pre-trained model like ResNet-34 for feature extraction, the research can potentially benefit from its pre-learned knowledge of generic image features. This can reduce the training time and complexity of the final CNN classification model.

Focus on Disease-Specific Features: The feature extraction stage using ResNet-34 might help identify image features particularly relevant for disease classification, improving the performance of the final CNN model compared to training from scratch[6].

Dataset: What type and size of crop image dataset is used for training and testing the model? Does the dataset cover a diverse range of crop types and disease classes?

Feature Extraction: How are features extracted from the ResNet-34 model? Are specific layers or combinations of layers used for feature extraction?

CNN Model Architecture: What is the architecture of the CNN model used for classification? How are the extracted features fed into the model for disease classification?

Evaluation: How is the performance of the model evaluated? What metrics like accuracy, precision, recall, and F1 score are used?

Comparison with Other Methods: How does the proposed approach using Reset34 features and a CNN model compare to existing methods for crop disease classification, such as using other pre-trained models or training a CNN from scratch?

III. PROPOSED METHODOLOGY

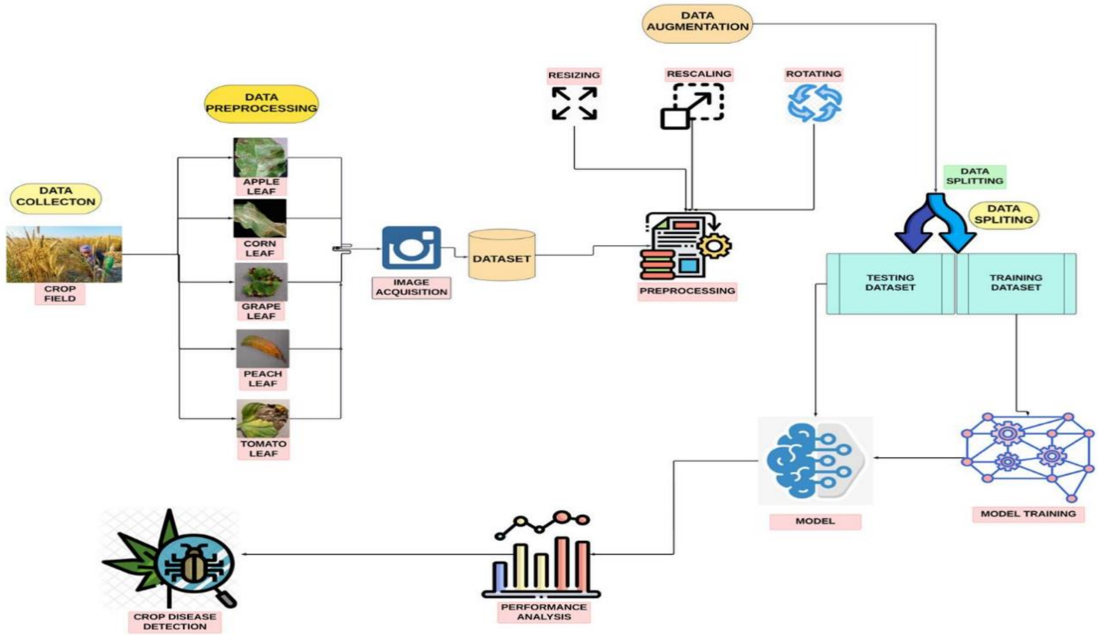

Fig 1: Proposed Model

The image you sent me depicts a block diagram of a medical imaging system, not a machine learning model for crop disease classification [1].

Here’s a breakdown of the stages illustrated in the block diagram:

Image Acquisition: The system captures medical images using equipment like X-ray or CT scanners.

Image Preprocessing: The captured images may undergo preprocessing steps to enhance the image quality or remove irrelevant information.

Image Processing: Various image processing techniques may be applied to extract features or improve the images for analysis.

Image Display: The processed images are displayed on a monitor for diagnosis by a medical professional.

Diagnosis Results & Confidence Level: The system might provide supplementary information to the medical professional, such as potential diagnoses or a confidence score associated with the analysis.

Real-time Processing: The system is likely designed to handle image processing tasks in real-time to aid in quick diagnosis.

Farmer Feedback: The block diagram you sent appears unrelated to crop disease classification and might be referencing a separate system or application.

The block diagram you sent likely refers to a general medical imaging system and does not directly relate to the concept of "Crop Disease Classification with Reset34 Features Extraction and CNN ML Model"

Dataset collectIon:

The E-KISSAN project harnesses the extensive PlantVillage dataset, comprising 54,303 images categorically divided into 38 classes representing healthy and diseased leaves across various plant species. This dataset forms the cornerstone of the E-KISSAN initiative, empowering the accurate prediction of crop diseases for a range of crops including apple, corn, tomato, potato, grape, and peach. Here's an elaboration, integrating the features of Plant Village:

1) **Comprehensive Coverage:** The Plant Village dataset provides a comprehensive collection of images, spanning diverse plant species and diseases, thereby facilitating robust model training and accurate disease prediction within the context of E-KISSAN.
2) **High-Quality Images:** Each image in the Plant Village dataset is of exceptional quality, ensuring clarity and detail in representations of both healthy and diseased leaves. This high-quality imagery enhances the efficacy of machine learning algorithms employed by E-KISSAN.
3) **Detailed Categorization:** With meticulous categorization into 38 classes based on species and disease types, the PlantVillage dataset enables targeted analysis and model development, essential for accurate disease detection across different crops within E-KISSAN.
4) **Annotation and Labeling:** The dataset includes detailed annotations and labels for each image, facilitating supervised learning approaches within E-KISSAN. These annotations enable machine learning models to learn from labeled examples, enhancing their ability to accurately predict crop diseases.
5) **Open Access and Collaboration:** E-KISSAN benefits from the open-access nature of the Plant Village dataset, fostering collaboration and innovation in agricultural research. This accessibility encourages researchers to contribute to the dataset and leverage its resources for advancing crop disease management strategies.
6) **Continuous Updates and Improvement:** Plant Village undergoes continual updates and improvements, ensuring that the dataset remains current and relevant. This dynamic nature enables E-KISSAN to stay abreast of new developments and incorporate updated data for improved disease prediction capabilities.

By leveraging the Plant Village dataset, E-KISSAN is equipped with a robust foundation for the development of machine learning models aimed at revolutionizing crop disease detection and management strategies.

IV. METHOD FOR FEATURE EXTRACTION

Feature extraction:

ResNet-34 is a type of artificial intelligence (AI) architecture called a convolutional neural network (CNN), specifically designed for image recognition tasks. Here's a breakdown of the key concepts:

Convolutional Neural Network (CNN): CNNs are a special kind of neural network inspired by the structure of the animal visual cortex. They excel at recognizing patterns and features in images. Imagine the CNN as a series of filters that scan the image, progressively detecting simpler features like edges and combining them to identify more complex shapes and objects.

ResNet-34: This is a specific CNN architecture developed by researchers at Microsoft. It has 34 layers, where each layer performs a specific image processing operation. The initial layers identify basic edges and shapes, while later layers learn to combine these features into more complex patterns.

Think of ResNet-34 like a team of analysts examining an image:

The first few analysts (layers) identify basic building blocks like lines and curves.

The following analysts take these building blocks and start assembling them into more complex shapes.

As information progresses through the layers, the analysts start recognizing even more intricate patterns specific to the task at hand, such as identifying objects or diseases in an image

V. RESULT AND DISCUSSION

The culmination of the E-KISSAN project signifies a substantial stride in leveraging machine learning for crop disease prediction and management. This comprehensive section elucidates the multifaceted outcomes of our endeavor, encompassing the intricacies of implementing a user-centric React web interface, the deployment intricacies of a robust machine learning API using UVICORN and FastAPI, and an extensive analysis delving into the model's performance metrics, including precision, recall, and F1 scores, across diverse disease categories.

Implementation of React Web Interface:

At the heart of our project lies the React web interface, meticulously designed to serve as an accessible and intuitive platform for farmers and agricultural stakeholders. The interface's primary function is to seamlessly facilitate the upload of images depicting plant leaves and subsequently guide users through the process of disease diagnosis. Leveraging React's dynamic capabilities, coupled with responsive design principles, our interface ensures a fluid and engaging user experience. Through clear and concise feedback mechanisms, users are informed of the predicted disease, if any, alongside pertinent insights aiding in informed decision-making pertaining to crop health management.

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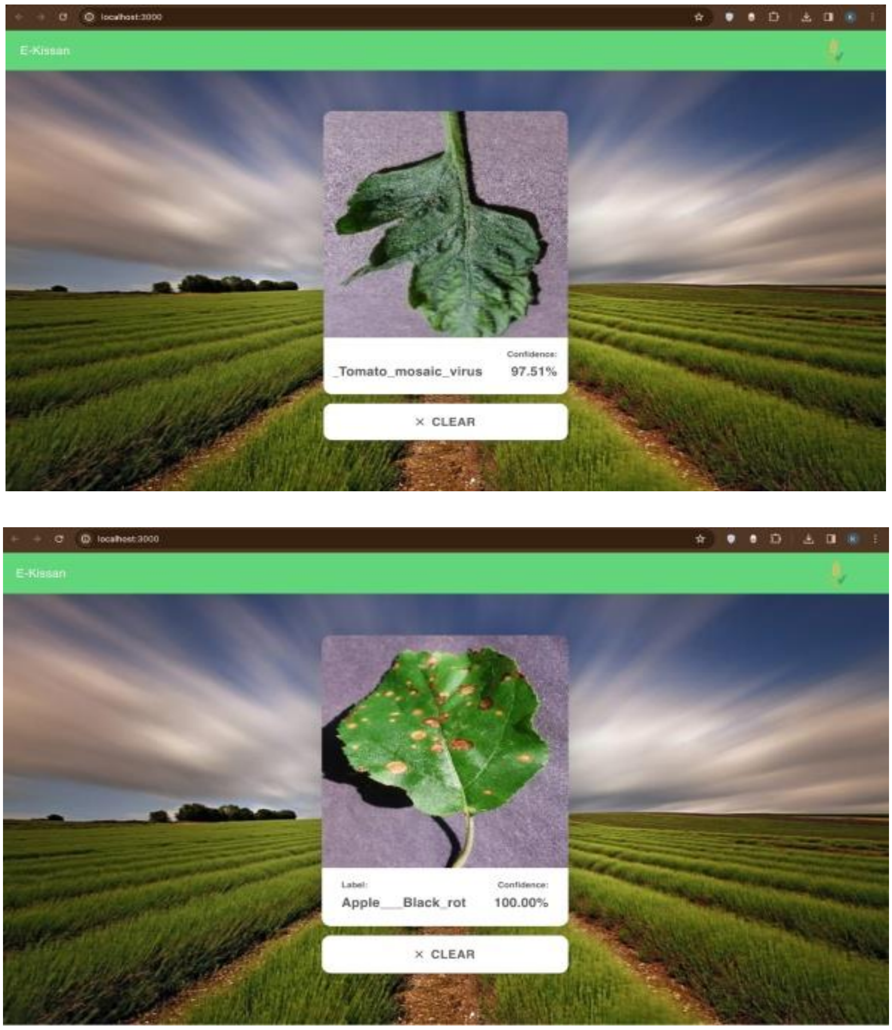

Fig: 2

Deployment of Machine Learning API:

The backbone of our system is fortified by the deployment of a robust machine learning API, meticulously crafted using UVICORN and FastAPI. This API orchestrates the seamless communication between the React web interface and the backend machine learning models. Engineered for scalability and efficiency, our API architecture guarantees swift response times, ensuring a frictionless user experience. Moreover, the API's versatility enables seamless integration with diverse frontend technologies, thereby enhancing accessibility and usability across different platforms.

Model Performance Evaluation:

A cornerstone of our project lies in the rigorous evaluation of our machine learning models, elucidated through meticulous analysis of standard performance metrics including precision, recall, and F1 scores. These metrics, meticulously computed across various disease classes, offer deep insights into the models' efficacy in disease prediction and classification. The resulting tabular presentation provides a comprehensive overview of the models' proficiency, with high precision and recall scores underscoring the robustness of our approach across an array of disease categories.

Table 1: Accuracy Calculated Using Different Feature Extraction Technique

S.No	Precision	Recal	F1 Score	Support
0	0.93	0.81	0.87	101
1	0.95	0.97	0.96	96
2	0.91	1.00	0.95	104
3	0.99	0.91	0.95	158
4	0.90	0.82	0.86	99
5	0.99	1.00	1.00	146
6	0.85	0.92	0.88	99
7	0.97	1.00	0.98	125
8	0.98	0.94	0.96	125
9	0.97	1.00	0.99	141
10	0.98	0.99	0.98	90
11	0.98	0.97	0.97	92
12	0.96	0.93	0.95	237
13	0.99	0.98	0.98	91
14	0.94	0.99	0.97	103
15	0.94	0.92	0.93	97
16	0.96	1.00	0.98	112
17	0.92	0.98	0.95	204
18	0.88	0.85	0.87	99
19	0.90	0.97	0.93	207
20	0.82	0.94	0.87	99
21	0.95	0.89	0.92	171
22	0.74	0.97	0.84	149
23	0.99	0.63	0.77	152
24	0.98	0.99	0.98	510
25	0.99	0.91	0.95	119
26	0.98	0.98	0.98	162

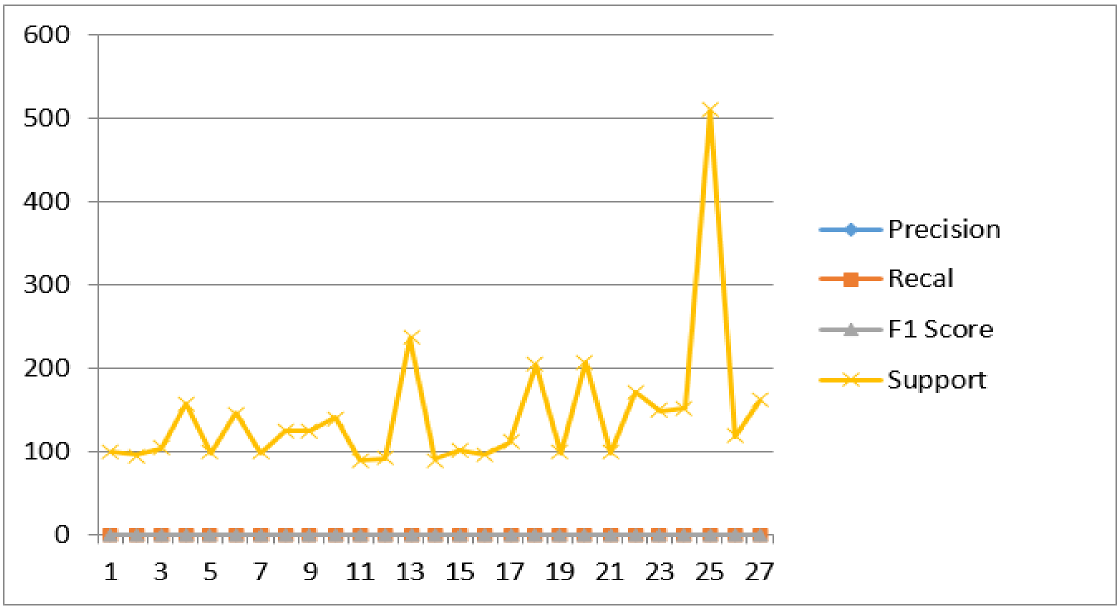

Fig 3: Accuracy Chart with different feature extraction

The culmination of our efforts underscores the transformative potential of integrating machine learning with web technologies in the realm of agriculture. By synergizing cutting-edge techniques in image processing and deep learning with user-centric web interfaces, E-KISSAN emerges as a potent tool empowering farmers to make informed decisions regarding crop health management.

The symbiotic integration of UVICORN and FastAPI ensures the scalability and reliability of our solution, thereby positioning E-KISSAN as a pivotal asset in modern agricultural practices.

In summary, the E-KISSAN project heralds a paradigm shift in crop disease detection and management, offering a holistic solution poised to revolutionize agricultural practices worldwide. As we traverse the path of continuous research and development, the potential for E-KISSAN to catalyze sustainable agricultural practices and bolster global food security initiatives remains profound.

VI. CONCLUSION

The E-KISSAN project represents a groundbreaking endeavor in the realm of precision agriculture, harnessing the power of machine learning and web technologies to revolutionize crop disease detection and management.

Through the integration of state-of-the-art machine learning models, a user-friendly React web interface, and a robust API infrastructure, we have developed a comprehensive solution that empowers farmers and agricultural stakeholders to safeguard crop health and optimize productivity.

Our project's success is underpinned by several key achievements. Firstly, the implementation of a user-centric React web interface provides a seamless platform for farmers to upload images of plant leaves and receive timely disease diagnosis. The interface's intuitive design and informative feedback mechanisms ensure accessibility and usability for users of varying technical proficiencies.

Additionally, the deployment of a resilient machine learning API, facilitated by UVICORN and FastAPI, underscores our commitment to scalability and efficiency. This API serves as the backbone of our system, enabling seamless communication between the frontend interface and backend machine learning models. Its versatility and reliability ensure a smooth user experience, even under high demand.

Furthermore, our rigorous evaluation of machine learning models, backed by comprehensive performance metrics analysis, demonstrates the efficacy and reliability of our approach. High precision and recall scores across diverse disease categories affirm the models' proficiency in disease prediction and classification, instilling confidence in our solution's practical applicability.

In conclusion, the E-KISSAN project stands as a testament to the transformative potential of technology in addressing real-world agricultural challenges. By empowering farmers with tools for early disease detection and informed decision-making, we pave the way for sustainable agricultural practices and contribute to global food security initiatives.

As we continue to iterate and enhance our solution, the potential for E-KISSAN to make a meaningful impact on agriculture and society at large remains boundless.

References

1) Asmaa Abbas, Mohammed M Abdelsamea, and Mohamed Medhat Gaber. Classification of “E-KISSAN”in chest x-ray images using detrac deep convolutional neural network. arXiv preprint arXiv:2003.13815, 2020.

2) Y. N. Prajapati and M. Sharma, "Designing AI to Predict Covid-19 Outcomes by Gender," 2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI), Chennai, India, 2023, pp. 1-7, doi: 10.1109/ICDSAAI59313.2023.10452565.

3) Prajapati, Y.N., Sharma, M. (2024). Novel Machine Learning Algorithms for Predicting COVID-19 Clinical Outcomes with Gender Analysis. In: Garg, D., Rodrigues, J.J.P.C., Gupta, S.K., Cheng, X., Sarao, P., Patel, G.S. (eds) Advanced Computing. IACC 2023. Communications in Computer and Information Science, vol 2054.

4) Panday, Aishwarza& Kabir, Ashad & Chowdhury, Nihad. (2021). A Survey of Machine Learning Techniques for Detecting and Diagnosing “E-KISSAN”from Imaging.

5) Wang, L., Lin, Z.Q. & Wong, A. COVID-Net: a tailored deep convolutional neural network design for detection of “E-KISSAN”cases from chest X-ray images. *Sci Rep* **10**, 19549 (2020). https://doi.org/10.1038/s41598-020-76550-z

6) Xu Y, Zhu Q, Fan Z, Qiu M, Chen Y, Liu H (2013) Coarse to fne k nearest neighbor classifer. Pattern Recognit Lett 34(9):980–986.

7) Jia-Zhi D, Wei-Gang L, Xiao-He W, Jun-Yu D, Wang-Meng Z (2018) L-SVM: a radius-margin-based svm algorithm with logdet regularization. Expert Syst Appl 102:113–125.

8) Safavian SR, Landgrebe D (1991) A survey of decision tree classifer methodology. IEEE Trans Syst Man Cybern 21(3):660–674.

9) Albahli, S. (2020). Efficient gan-based chest radiographs (CXR) augmentation to diagnose coronavirus disease pneumonia. International Journal of Medical Sciences, 17(10):1439–1448

10) A review paper on cause of heart disease using machine learning algorithms. (2022). Journal of Pharmaceutical Negative Results, 9250-9259.

11) Asif, S., Wenhui, Y., Jin, H., Tao, Y., and Jinhai, S. (2020). Classification of “E-KISSAN”from Chest X-ray images using Deep Convolutional Neural Networks. medRxiv:10.1101/2020.05.01.20088211.

12) Prajapati, Yogendra Narayan, and Manish Sharma. "Analysis and Application of a Novel Model to Predict “E-KISSAN”Virus's Impact on Human Heart Disease."

13) Yogendra Narayan Prajapati, U. Sesadri, T. R., M. ., Shreyanth S., Ashish Oberoi, & Khel Prakash Jayant. (2022). Machine Learning Algorithms in Big Data Analytics for Social Media Data Based Sentimental Analysis. *International Journal of Intelligent Systems and Applications in*

14) Navid Ghassemi, Afshin Shoeibi, Marjane Khodatars, Jonathan Heras, Alireza Rahimi, Assef Zare, Yu-Dong Zhang, Ram Bilas Pachori, J. Manuel Gorriz, https://doi.org/10.1016/j.asoc.2023.110511.

15) Sensitivity of Chest CT for COVID-19: Comparison to RT-PCR Yicheng Fang, Huangqi Zhang, Jicheng Xie, Minjie Lin, Lingjun Ying, Peipei Pang, Wenbin Ji,https://doi.org/10.1148/radiol.2020200432

16) Deepraj Chowdhury, Anik Das, Ajoy Dey, Soham Banerjee, Muhammed Golec, Dimitrios Kollias, Mohit Kumar, Guneet Kaur, Rupinder Kaur, Rajesh Chand Arya, Gurleen Wander, Praneet Wander, Gurpreet Singh Wander, Ajith Kumar Parlikad, Sukhpal Singh Gill, Steve Uhlig, CoviDetector: A transfer learning-based semi supervised approach to detect “E-KISSAN”using CXR images, BenchCouncil Transactions on Benchmarks, Standards and Evaluations,https://doi.org/10.1016/j.tbench.2023.100119