

SPECIAL FEATURE

Fingerprint Pattern
Analysis for Blood
Group Detection

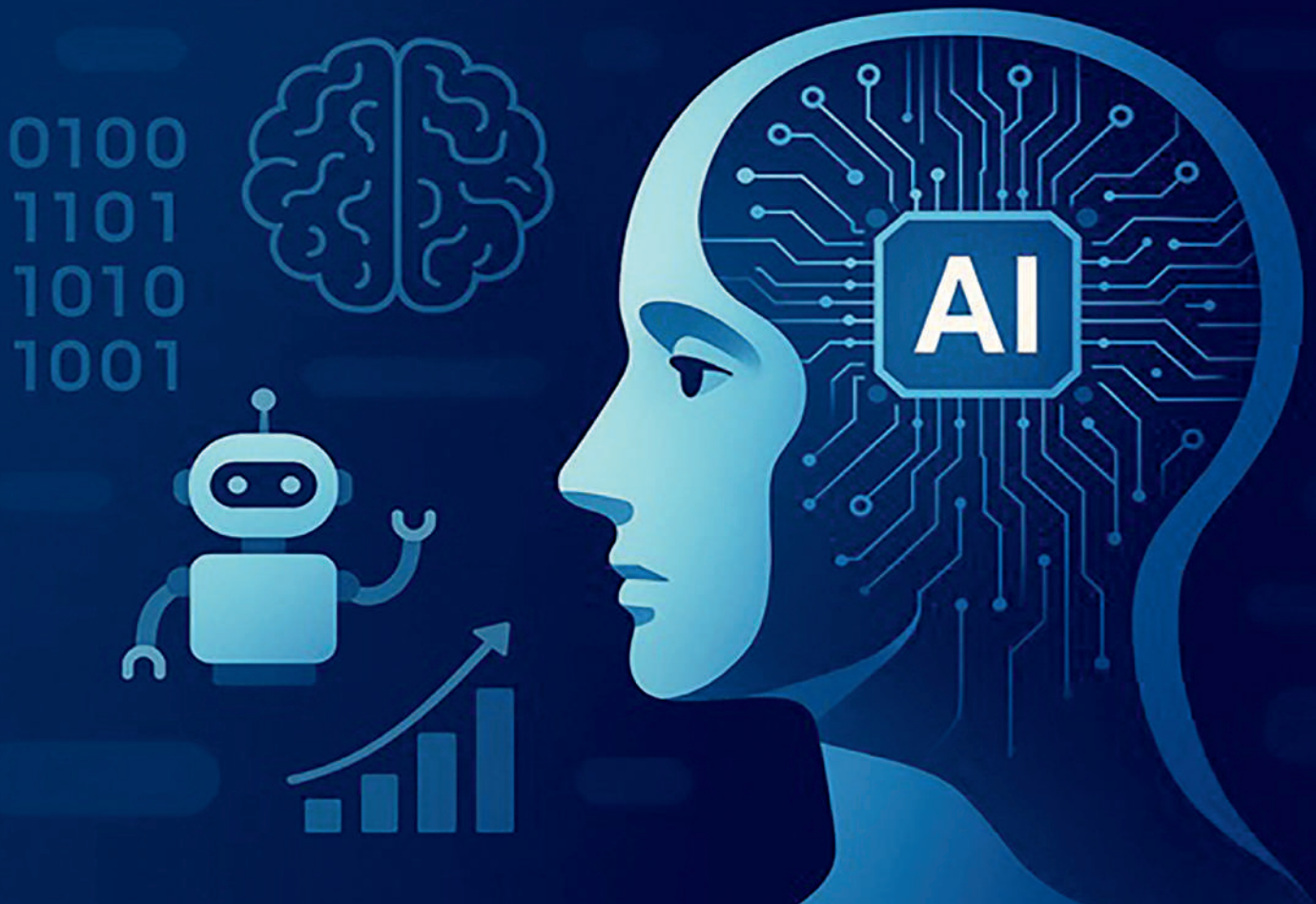


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Our Mission: "To provide the best of technical skills, professional ethics and human values in enriching the disciplines of Sciences, Engineering and Technology for Social development and Nation building".

From Code to Conscience: Why Artificial Intelligence Needs Human Intelligence

A once science-fiction concept and a background process, it is now fundamental to modern existence and a reality today. Walk into any classroom, laboratory, or community space in educational institutions, and one of the newest terms rings out loudly, that of Artificial Intelligence (AI). Starting with chatbots which can be utilized in order to complete academic tasks and further reaching to more advanced algorithms which can propose our watching preferences, the decisions we make about buying anything, and even our ideas, AI has become a nice addition to the landscape of our lives. With the current advancement of AI, as it grows in its level of intelligence, speed, and autonomy, the key question is the following: Are we teaching machines more than we are becoming responsible thinkers? The advances in AI technology are quite impressive indeed.

The modern machine learning models have the capability of diagnosing medical issues, improving energy management, detecting cybersecurity attack, and driving self-driving cars. In the engineering field, AI is transforming the design processes, years of experimentation are condensed into several weeks of predictive analysis and simulation. To students this change means accessing previously unimaginable resources that can be used to increase creativity, productivity and innovation. However, every new technological breakthrough places a dark cloud of doubt. It is necessary to point out that algorithms are not objective per se. They base their learning on information, which is usually a manifestation of the innate human prejudices- whether social, economic, or even cultural. What is dangerous is not the direct substitution of human labour but rather the possibility to give up judgment without properly questioning the implications.

One of the main spheres of influence is automation. In spite of the fact that AI-based systems improve productivity, they also transform the labour markets. Conventional work is on the decline, leading to a growing requirement of interdisciplinary and multi-skilled sets. Coding skills are also necessary, but not enough; contextual situational factors are also important. Another critical area is privacy issues. We are seeking convenience and in the process, we leave long digital footprints without meaning to. Facial recognition, predictive policing, and targeted marketing form the technologies that raise unsettling questions: Who owns our data? Who decides where it is applicable? And who is responsible in the case of algorithmic failures? Here, students will play a very crucial role as the future generation of engineers, researchers, and policy formulators.

AI is not to be perceived as something unintelligible, that just works according to its own logic. It merits examination, control and intentional direction. Those who use AI in the future will not make it how it becomes; it will be people who understand its limitations and is shaping its future. The ultimate dilemma is not that more intelligent machines are created but that wise humans are developed.

The innovations that lack moral concerns are the ones that will create a blistering advancement with no significant guidance. As the digital era advances, the focus must shift from examining what capabilities AI possesses to understanding the ethical responsibilities it entails and the stakeholders responsible for governing its use. By addressing these considerations, we can ensure that intelligence whether human or artificial serves to benefit humanity rather than undermine it.

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Fingerprint Pattern Analysis for Blood Group Detection

Abstract – Blood group detection is essential in medical diagnostics, especially for transfusions, organ transplants, and prenatal care. Traditional blood typing relies on serological methods, which, although accurate, are invasive and require laboratory infrastructure. This research investigates a non-invasive alternative approach utilizing fingerprint image processing. Unique ridge patterns and minutiae points in fingerprints have shown potential correlations with specific blood group phenotypes. By applying advanced image processing techniques and Convolutional Neural Networks (CNNs), this model accurately predicts blood groups from fingerprint images. Trained on a large dataset of labeled fingerprint samples, the CNN demonstrates high reliability in classifying blood types. This approach offers a rapid, accessible, and non-invasive solution compared to conventional methods, reducing dependency on skilled personnel and laboratory resources. The integration of biometric data with medical diagnostics could significantly streamline healthcare delivery and open new possibilities for both medical and forensic applications.

Keywords— Blood Group Detection, Medical Diagnostics, Fingerprint Image Processing, Ridge Patterns, Minutiae Points.

I. Introduction

The most reliable and unique feature of human identity is the fingerprint pattern. The fingerprint pattern cannot be changed and remains as is till death of an individual. Till date, in the cases of event considerations, fingerprint proof is considered the most important evidence even in the court of law. The minutiae pattern of each human is different, and the chance of having similarity is very small, almost one in sixty-four thousand million. The minutiae pattern is different even for twins. The ridge pattern is also unique and remains unchanged from the birth of the individual. The blood bunch is a natural trademark that isn't changed during the lifetime of a person. The primary issue for creating a blood bunch forecast technique is non-comprehensiveness of various examples of unique mark modalities. Examination throws almost no light on blood bunch forecast and various infections that accompany maturing, especially if fingerprints are taken as a biometric methodology.

II. Literature survey

Fingerprint patterns are stable and unique, making fingerprint-based biometric identification a reliable and widely used method for personal authentication. Recently, its application has extended beyond security systems to explore its potential in medical prediction, particularly for blood group identification and health condition analysis.

Vijay Kumar and Patil N [1] demonstrated promising correlations between fingerprint patterns and blood group classification. Their study employed machine

learning techniques, specifically Multiple Linear Regression with Ordinary Least Squares (OLS), achieving an accuracy of 62% in predicting blood groups based on fingerprint minutiae. Although encouraging, the study highlights the need for larger datasets and additional features to improve prediction accuracy.

Further research by D. R. Ingle, Patil, and Vijay Kumar [2] explored associations between fingerprint characteristics and biological markers, linking them to age-related conditions such as type 2 diabetes, arthritis, and hypertension. Their work suggests the potential of fingerprints in early disease detection.

Ali, Mouad MH, et al. [3] focused on systematic fingerprint processing, including pre-processing, minutiae extraction, and matching techniques using Euclidean distance for both (1:1) and (1:N) scenarios. Advances in feature extraction methods, such as BGP descriptors and GaborHoG filters proposed by Alshehri et al. [4], have further enhanced recognition accuracy and system reliability.

Additional studies [5] confirmed correlations between fingerprint patterns, blood groups, and other biological traits, reinforcing the biological relevance of dermatoglyphics and their applicability in forensic and medical domains.

Despite these advancements, limitations such as small sample sizes and population-specific studies restrict generalizability. Overall, fingerprint analysis shows strong potential for both biometric identification and biomedical applications, warranting further research with larger, diverse datasets and advanced analytical techniques.

III. Methodology

The process of blood group determination through fingerprint analysis begins with the user interacting with the system via a dedicated user interface is shown in Fig. 1.

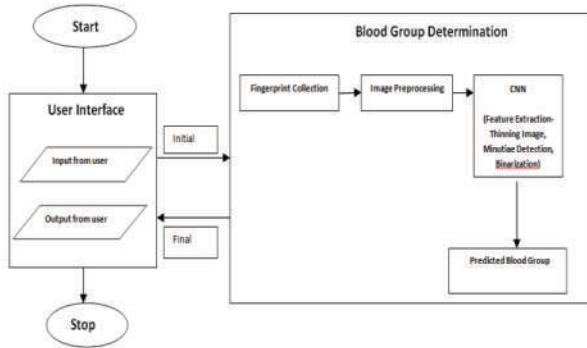


Fig. 1 Blood Group Determination Process

The user provides their fingerprint as input, which is then captured and forwarded to the internal processing unit of the system. The first stage involves the collection of the fingerprint image, which, for this research, is sourced from an openly available dataset on Kaggle. Once the fingerprint image is acquired, it undergoes a pre-processing phase including Ridge Segmentation, Histogram Equalization and Binarization, where it is enhanced by eliminating noise and improving clarity to facilitate accurate feature extraction. Following this, the system performs feature extraction to identify and isolate significant fingerprint characteristics such as ridges, bifurcations, and minutiae points. The extracted features are subsequently analysed by a Convolutional Neural Network (CNN) using Lec Network (LeNet) and Residual Network (ResNet) model which has been trained to learn the correlation between specific fingerprint patterns and blood group classifications. Upon completion of the analysis, the system predicts the most likely blood group associated with the provided fingerprint. Finally, the predicted result is communicated back to the user via the user interface, thereby concluding the operation of the system. The basic goal and objective of this work is to detect blood groups using fingerprint patterns. LeNet and ResNet Model have been used to predict the blood group of different classes using fingerprint pattern with 60% and 70% accuracy respectively.

IV. Result Analysis

The training accuracy of ResNet model in the Fig. 2

shows an overall upward trend with noticeable fluctuations across epochs. The validation accuracy is unstable, with sharp drops and spikes, indicating inconsistent generalization. In Fig. 3 the training loss steadily decreases, suggesting effective learning on the training data where the validation loss exhibits large spikes at certain epochs, pointing to overfitting or sensitivity to validation samples.

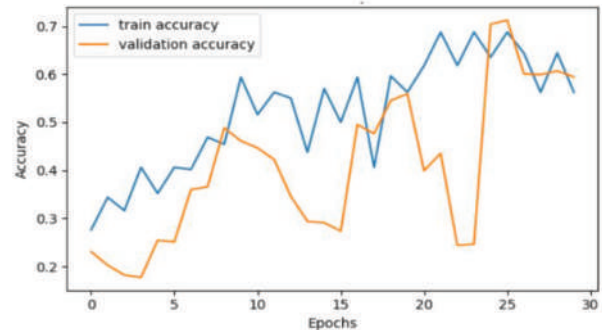


Fig. 2 Accuracy Graph of ResNet Model

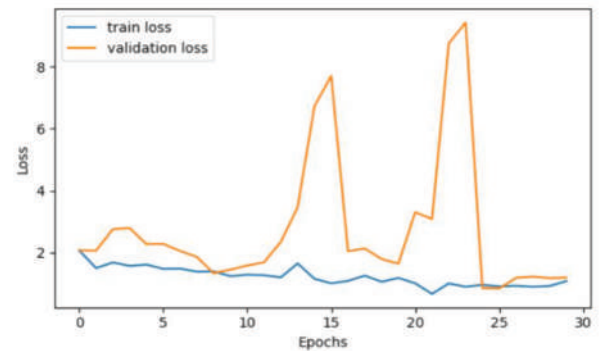


Fig. 3. Loss Graph of ResNet Model

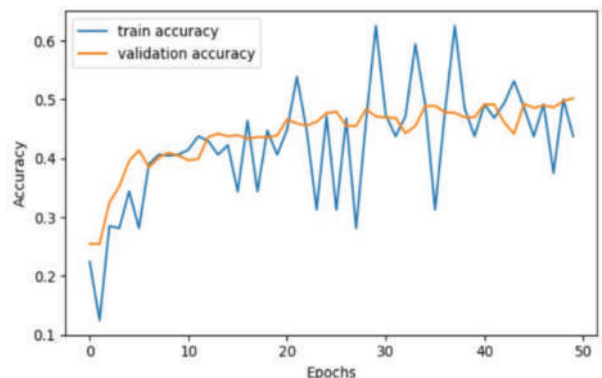


Fig. 4 Accuracy Graph of LeNet Model

LeNet gradually improves training accuracy as shown in Fig. 4 but Validation accuracy is smoother and closely follows training accuracy, indicating stable learning. The training loss consistently decreases with minor fluctuations over epochs in the Lenet model and remaining close to training loss of ResNet model as shown in Fig. 5.

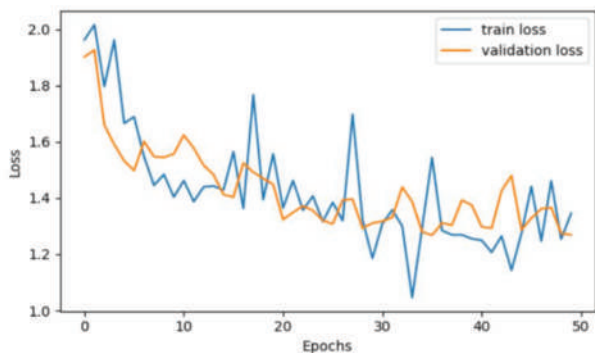


Fig. 5 Loss Graph of LeNet Model

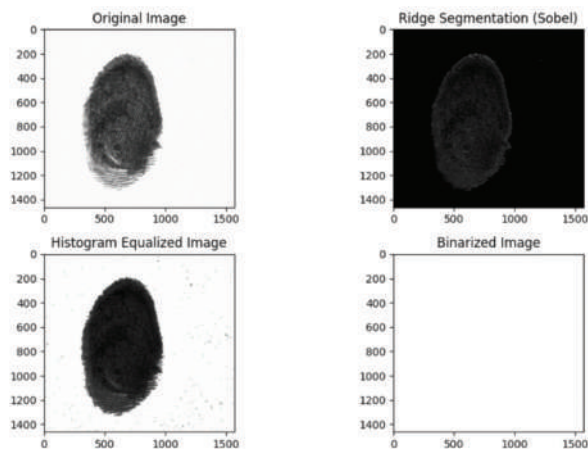


Fig.6. Original and Preprocessed image

In comparison, ResNet achieves higher peak accuracy suffers from unstable validation and shows signs of overfitting. LeNet demonstrates better training-validation consistency.

The Fig. 6 shows original image and preprocessed image which included Ridge Segmentation using Sobel, Histogram Equalization and Binarization.

Table.1. Accuracy & Loss of LeNet and ResNet Model

Model	Accuracy	Loss
LeNet	~60%	2.15
ResNet	~70%	1.44

Table 1 quantifies the result of both ResNet and LeNet. The accuracy of ResNet is better than LeNet and loss is also less than LeNet.

V. Conclusions

The model proves that fingerprint analysis can predict blood groups with high accuracy. It outperforms traditional methods in speed and accessibility.

Compared to traditional blood group testing methods, which require blood samples, chemical reagents, and laboratory infrastructure, this fingerprint-based approach offers a faster, cost-effective, and non-invasive alternative. The primary objective was to determine whether a significant relationship exists between fingerprint patterns and blood groups. It has limitations like dependency on high-quality fingerprint images smaller dataset for rare blood types.

VI. Acknowledgment

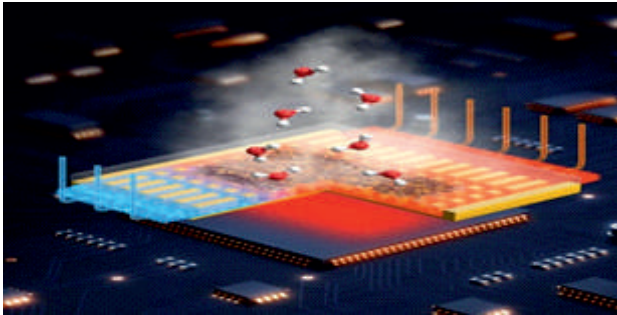
We would like to express our sincere thanks and heartfelt gratitude to Asst Prof. Sharmistha Puhan, for her constant encouragement, insightful suggestions, and continuous support. Her guidance has been a great source of motivation and has been played a vital role in shaping this research work from the very beginning to its completion.

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AI is Overheating could be fixed



The need for data processing and the associated heat are growing along with artificial intelligence (AI) and cloud computing. Up to 40% of the energy used in a data center nowadays is used for cooling. By 2030, the world's energy demand for cooling might more than triple if current development continues. In order to significantly improve the energy efficiency of data centers and high-performance electronic equipment, a novel method is designed a fiber membrane that uses evaporation to naturally remove heat. In addition to offering an efficient and energy-efficient substitute for traditional cooling techniques like fans, heat sinks, and liquid pumps, it may also lessen the significant water use of many current systems.

Source: Scitech Daily

Athena: Nasa's fastest-ever supercomputer



NASA has introduced Athena, its most powerful supercomputer yet, which dramatically improves its ability to process complicated scientific and technical data. On January 14, 2026, Athena was officially made operational for all permitted users. The system was launched through NASA's Advanced Supercomputing facility, which supports high-performance computing demands across all NASA projects. The supercomputer is comprised of 1,024 processing nodes, each powered by two 128-core AMD EPYC "Turin" processors. This yields 256 physical cores per node and over 2.64 lakh total cores across the system.

At peak performance, Athena can deliver over 20 petaflops, or more than 20 quadrillion calculations per second.

Source: The Indian Express

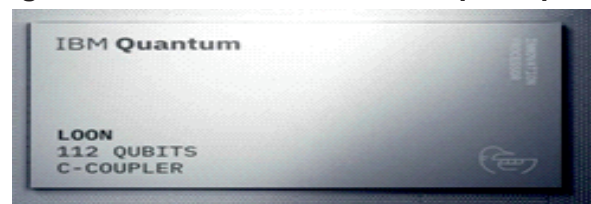
Dragonwing IQ-10 chip for humanoid robots



Qualcomm's Dragonwing IQ-10, the company's first processor designed particularly for robotics, capable of rapidly handling complicated tasks while supporting scalable robot designs. Qualcomm displayed it at the India AI Impact Summit 2026. Qualcomm also showcased a modular robotics architecture that combines edge computing, machine learning, and an AI data flywheel, allowing robots to learn and adapt continuously. To accelerate commercial adoption, the company will initially focus on ten high-impact jobs in logistics, manufacturing, and retail, leveraging its experience with Advance Driver Assistance Systems (ADAS) and multi-criticality AI systems.

Source: The Indian Express

Nighthawk and Loon Quantum Chips chip

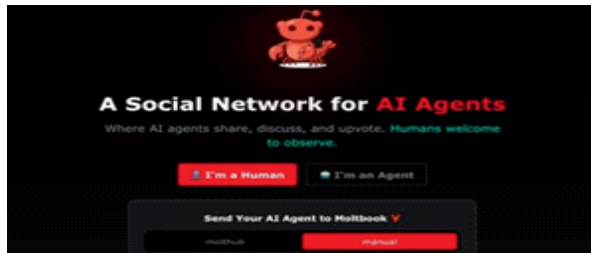


Quantum Nighthawk, IBM's most recent quantum processor, is intended to produce circuits that are 30% more complex than earlier iterations. By the end of 2025, users should receive the CPU, which has 218 adjustable couplers and 120 qubits. Additionally, IBM unveiled Quantum Loon, an experimental processor that shows every piece of hardware needed for fault-tolerant quantum computing. The company completed the milestone a year ahead of schedule by leveraging classical computer gear to accomplish a

tenfold speed-up in quantum error correction decoding. The goal of the advancements is to achieve fault-tolerant quantum computing by 2029 and quantum advantage by 2026. According to IBM, verifiable demonstrations of quantum advantage are expected by 2026, and future iterations of the Nighthawk processor will reach up to 15,000 two-qubit gates by 2028.

Source: Tech Magazine

Moltbook



A few years ago, the idea of a social media platform meant exclusively for artificial intelligence (AI) agents would have sounded unrealistic. But today, this concept has turned into reality with Moltbook, a social network created solely for AI bots. Humans are not allowed to post or interact on the platform—they can only observe. Over the past few weeks, platforms like Reddit and X have been filled with discussions, screenshots, and reactions related to Moltbook. Names such as Moltbot, Clawdbot, and OpenClaw—essentially referring to the same project—have been repeatedly mentioned, sparking widespread curiosity.

This emerging phenomenon is attracting attention not only from casual internet users and AI enthusiasts, but also from researchers, developers, and technology observers. In simple terms, Moltbook can be described as a social network designed entirely for virtual bots to communicate among themselves.

Source: The Indian Express

Project Genie

Google has introduced Project Genie, to create rich and interactive virtual environments using artificial intelligence (AI). A user begins by describing the environment and characters through text prompts. They can also upload or generate images to decide how the virtual world should look. A user can preview and fine-tune the scene using Google's AI tools, such as Nano Banana Pro and Gemini. Once everything



looks satisfactory, the user can step into the environment and explore it either from a first-person or a third-person perspective. Inside these AI-generated worlds, characters are not static. They can walk, fly, or even drive across landscapes that keep expanding as the user moves forward. Another key feature is its memory areas that have already been visited remain visually consistent when the user returns, making the experience feel more realistic and immersive.

Source: The Indian Express

Multi-Channel Streaming Amplifier



Sonos has announced a new product that directly addresses the rising demand for smarter, cleaner, and more adaptable home audio solutions. This device is a professional-grade, multi-channel streaming amplifier built for modern homes that are larger, more open, and constantly changing in how their spaces are used. While it builds on the foundation of the standard Sonos Amp, this new model is designed for far more complex audio setups. It has been developed in close collaboration with professional installers and system integrators, who increasingly deal with homes featuring multiple audio zones, high speaker counts, and evolving layouts. According to Sonos, the objective was straightforward—to make powerful, large-scale home audio systems easier to plan, install, and manage on a day-to-day basis.

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Plant Disease Detection System using CNN

Abstract – Crop yield loss due to plant diseases is a persistent and critical challenge in the agricultural sector, especially in agrarian economies like India, where a substantial portion of the population relies on farming for their livelihood. Traditional methods of plant disease detection often involve manual inspection, which is time-consuming, labor-intensive, and requires expert knowledge—factors that render it impractical for large-scale monitoring and early intervention. In this paper, we propose a robust, automated plant disease detection system that leverages the power of deep learning, specifically Convolutional Neural Networks (CNNs) and Vision Transformer (ViT) models, to accurately identify plant diseases from leaf images. The system is trained and evaluated using a large-scale dataset comprising over 80,000 RGB images categorized into 38 distinct plant disease classes. The CNN architecture was developed and fine-tuned across multiple iterations, ultimately resulting in a best-fit model that achieved an outstanding classification accuracy of 97% with a corresponding F1-score of 0.97. In parallel, a Vision Transformer model was implemented, which processes images by dividing them into patches and applying self-attention mechanisms. Although the ViT model demonstrated strong theoretical capabilities in capturing global image features, it achieved a relatively lower accuracy of 89%, mainly due to its higher data dependency and training complexity. To enable real-world applicability, the trained CNN model was integrated into a lightweight and interactive web-based application developed using Streamlit. This platform allows end-users, particularly farmers and agricultural officers, to upload leaf images and instantly receive disease predictions along with detailed information and suggested treatments. The interface is designed to be user-friendly and accessible without requiring any technical background. The proposed solution not only achieves high accuracy and efficiency but also emphasizes scalability, cost-effectiveness, and ease of deployment. By bridging the gap between deep learning research and field-level agricultural applications, this system can serve as a valuable tool in early disease detection, timely intervention, and improved crop health management. Ultimately, it contributes to reducing yield losses, minimizing pesticide misuse, and enhancing sustainable farming practices.

Keywords – Plant disease detection, Convolutional Neural Networks (CNN), Vision Transformer (ViT), deep learning, image classification, precision agriculture, crop monitoring.

I. Introduction

Agriculture is not only a primary occupation for a large segment of India's population but also a significant contributor to the country's economy. As per recent statistics, nearly 70% of the rural population in India relies on agriculture either directly or indirectly for their livelihood. However, plant diseases continue to be a major obstacle to agricultural productivity, leading to substantial economic losses and affecting food security. The problem is further exacerbated by climate change, which alters the behavior of pathogens and increases the vulnerability of crops.

Early and accurate detection of plant diseases is crucial for timely intervention, which can significantly mitigate crop damage and prevent disease spread. Traditional methods of disease diagnosis involve manual inspection by experienced agronomists or pathologists. While effective on a small scale, these methods are impractical for large-scale farms due to their dependency on human labor, requirement of specialized expertise, and time-consuming nature. Additionally, delays in diagnosis often lead to the unnecessary application of pesticides, affecting both

crop quality and environmental health.

To address these limitations, automated approaches using image processing and machine learning have emerged as powerful alternatives. These methods involve analyzing leaf images to identify visual symptoms such as color changes, texture irregularities, and lesion patterns. By training models on large datasets of labeled leaf images, machines can learn to recognize various plant diseases with impressive accuracy and efficiency.

Recent advancements in deep learning have further enhanced the capability of such systems. Convolutional Neural Networks (CNNs), known for their feature extraction capabilities in image data, have shown remarkable success in classifying plant diseases. Meanwhile, Transformer models, especially the Vision Transformer (ViT), have introduced a novel architecture that models global relationships between image patches using self-attention mechanisms. Although CNNs are computationally efficient and widely used, Transformer models offer promising results in capturing complex features and spatial dependencies.

In this paper, we present a comprehensive study and implementation of an image-based plant disease detection system using both CNN and Transformer models. The system was trained on a dataset containing over 80,000 leaf images across 38 disease classes. We evaluate and compare the performance of the models and deploy the best-performing one through a web-based interface developed using Streamlit. This system provides a cost-effective, accurate, and scalable solution that can assist farmers in identifying crop diseases early, thereby enabling better disease management and improved agricultural productivity.

II. Literature Survey

The identification and classification of plant diseases have significantly evolved with the integration of image processing and deep learning techniques. Traditional approaches relied on expert inspection, whereas modern systems enable automated detection using visual data and computational models.

Early methods, such as the work by Khirade and Patil [1], used Otsu's thresholding for image segmentation, followed by feature extraction (color, texture, morphology) and classification using Back propagation Neural Networks (BPNN). While effective for small datasets, these approaches depended heavily on handcrafted features and lacked scalability. Similarly, Madiwalar and Wyawahare [2] applied texture and color-based features with Support Vector Machines (SVM), achieving 83.34% accuracy. However, manual feature selection limited adaptability and performance.

Moghadam et al. [3] introduced hyper spectral imaging with k-means clustering, achieving 93% accuracy. Despite high precision, the requirement of expensive hyper spectral sensors restricted practical deployment. With the advancement of deep learning, Shrestha et al. [4] implemented a Convolutional Neural Network (CNN), achieving 88.8% accuracy. However, issues such as class imbalance and low F1-score indicated limitations in model generalization.

Overall, existing systems face challenges including reliance on handcrafted features, limited datasets, high computational or hardware costs, and suboptimal performance in real-world conditions.

To address these issues, the proposed approach utilizes a large and diverse dataset (80,000+ images), employs both CNN and Vision Transformer (ViT) architectures for improved feature learning, and integrates a web-based platform for real-time disease detection. This ensures higher accuracy, scalability, and practical usability in agricultural applications.

III. System Design and Implementation

A. Dataset

A publicly available dataset containing over 80,000 high-resolution RGB images of plant leaves, categorized into 38 different disease classes, was used for this study. The dataset was divided into 80% for training and 20% for validation. To prepare the data, the images were first converted from BGR to RGB format. Each image was resized to 128×128 pixels to standardize input size and optimize GPU memory usage. Pixel values were normalized to a 0–1 scale using Equation (1)

$$I_{norm}(x, y) = \frac{I(x, y)}{255} \dots\dots\dots (1)$$

Images were then converted into NumPy arrays and subsequently transformed into tensors for compatibility with TensorFlow and PyTorch. Data augmentation was applied on-the-fly during training to enhance generalization through techniques like rotation, flipping, and brightness adjustment.

B. CNN Model

Three CNN models were created and evaluated. Model 1 was an overfitting-prone architecture with multiple convolutional layers and no dropout regularization, which led to excellent training accuracy but poor validation results. Model 2 was shallow with excessive dropout, leading to underfitting and poor overall performance. Model 3, the best-fit model, was a balanced architecture consisting of three convolutional-pooling blocks followed by a fully connected dense network. Each convolutional block included a 3×3 kernel, ReLU activation, and a 2×2 max-pooling layer. Dropout (0.25–0.5) was used after each block to reduce overfitting. The final layers included flattening, a dense layer with 128 neurons, and a softmax output layer with 38 units for classification. Fig. 1 shows the CNN architecture.

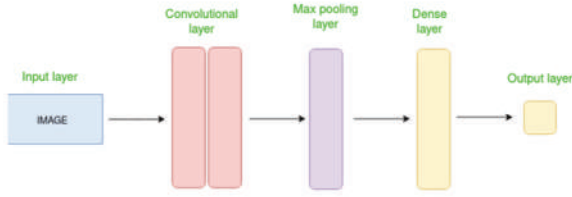


Fig. 1 CNN block diagram

C. Transformer Model

The Vision Transformer (ViT) was implemented for comparison. Unlike CNNs, ViT models operate by treating image patches as tokens. Fig. 2 depicts the overall architecture of the vision transformer model used in this study. Each 128×128 image was divided into 64 patches of size 16×16. Each patch was flattened into a vector and passed through a linear projection to generate a 64-dimensional embedding. Positional embeddings were added to maintain spatial structure. The sequence of 64 tokens was processed using four Transformer encoder layers, each containing multi-head self-attention and feedforward layers.

Finally, the output token embeddings were passed through an MLP with hidden layers of size 128 and 64, ending in a softmax classifier.

D. Specifications of Machine

The models were developed using Python 3.10.16. CNNs were trained in TensorFlow, while ViTs were implemented using PyTorch and HuggingFace Transformers. Preprocessing was handled using OpenCV and NumPy. The system used included an Intel i5 12th Gen processor, 8GB RAM, 512GB SSD,

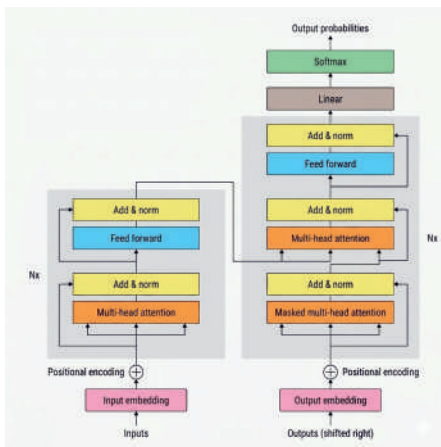


Fig. 2 Vision Transformer model Architecture

and an NVIDIA RTX 3050 GPU with 4GB VRAM. Model training was efficient, and CNN inference time was under 0.2 seconds per image, making it suitable for real-time deployment.

E. Deployment

A lightweight web application was developed using Streamlit to deploy the trained CNN model. The web interface allows users to upload images through a browser, processes them using the trained model, and returns the predicted disease class along with confidence scores. The interface has three main sections: (i) image upload, (ii) prediction display, and (iii) disease detail page showing the description and possible remedies. This made the solution accessible to non-technical users such as farmers and agricultural workers.

F. Model Evaluation

The best-fit CNN model was evaluated using classification metrics derived from the confusion matrix. The confusion matrix is a 38×38 square matrix where the diagonal entries indicate correct predictions. Metrics such as accuracy, precision, recall, and F1-score were calculated using Equations (2 to 5).

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad \dots\dots\dots (2)$$

Precision per class:

$$\text{Precision}_i = \frac{TP_i}{TP_i+FP_i} \quad \dots\dots\dots (3)$$

Recall per class:

$$\text{Recall}_i = \frac{TP_i}{TP_i+FN_i} \quad \dots\dots\dots (4)$$

F1-score per class:

$$F1_i = 2 \cdot \frac{\text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i} \quad \dots\dots\dots (5)$$

To handle class imbalance, macro-averaged metrics were computed using Equations (6 to 8)

$$\text{Macro} = \frac{1}{C} \sum_{i=1}^C \text{Precision}_i \quad \dots\dots\dots (6)$$

$$\text{Macro} = \frac{1}{C} \sum_{i=1}^C \text{Recall}_i \quad \dots\dots\dots (7)$$

$$\text{Macro} = \frac{1}{C} \sum_{i=1}^C F1_i \quad \dots\dots\dots (8)$$

where $C=38C=38C=38$.

III. Result Analysis

A. CNN Model Evaluation

This section presents a comparative evaluation of two deep learning models—Convolutional Neural Networks (CNN) and Vision Transformers (ViT)—applied to plant disease detection. The CNN model was designed and tested in three configurations. The first configuration, Model 1, included a large number of convolutional layers without any dropout regularization. While it achieved high accuracy during training, the validation performance degraded significantly, showing clear signs of overfitting. Model 2 used a shallow architecture with fewer layers and high dropout, resulting in poor performance on both training and validation sets, indicating underfitting due to limited feature extraction.

Model 3 was constructed with balanced depth, dropout regularization, and an appropriate learning rate. It comprised three convolutional-pooling blocks with 3×3 kernels, ReLU activation functions, and 2×2 max-pooling layers, followed by a dense layer with 128 neurons and a softmax output layer for 38-class classification. This best-fit CNN model achieved the highest validation accuracy of 97% and an F1 score of 0.97, demonstrating strong generalization and reliable class-wise predictions across the dataset.

Table –1: Metric Evaluation Table for CNN model

Metric	Model 3(Perfectly fit)	Model 2(Overfit)	Model 1(Underfit)
Accuracy	0.97	0.25	0.07
Macro Avg Precision	0.97	0.30	0.17
Macro Avg Recall	0.97	0.25	0.07
Macro Avg F1-Score	0.97	0.20	0.06
Weighted Avg Precision	0.97	0.35	0.17
Weighted Avg Recall	0.97	0.25	0.07
Weighted Avg F1-Score	0.97	0.22	0.06

B. Transformer Model Evaluation

The Vision Transformer model was implemented as a parallel approach to evaluate the performance of global attention-based architectures. In this model, each image of size 128×128 was divided into 64 patches, each measuring 16×16 pixels. Each patch was flattened and passed through a linear layer to obtain a 64-dimensional embedding. These embeddings were then augmented with positional encodings and passed through four encoder layers, each containing four self-attention heads and a feedforward network. The output

tokens were processed through a Multi-Layer Perceptron consisting of hidden layers with 128 and 64 neurons, followed by a softmax layer. The Transformer model achieved a final accuracy of 89% and an F1-score of 0.89. Although the model successfully captured global contextual features using self-attention, its performance lagged behind the CNN model due to higher computational complexity, slower convergence, and a need for larger datasets.

Table – 2: Metric Evaluation Table for Transformer models

metric	precision	recall	F1-score	support
accuracy	-	-	0.89	17572
Macro avg	0.89	0.89	0.89	17573
Weighted avg	0.89	0.89	0.89	17572

C. Confusion Matrix Analysis

To understand class-wise performance, confusion matrices were generated for all CNN configurations and the Transformer model. Model 1 showed a concentration of correct predictions along the diagonal but significant misclassifications elsewhere, which reflected its overfitting behavior. Model 2’s matrix displayed low diagonal values and dispersed errors, indicating underfitting. Model 3’s confusion matrix showed a distinct and strong diagonal with very few off-diagonal entries, confirming highly accurate predictions across all 38 disease classes. In the case of the Vision Transformer, the confusion matrix was moderately diagonal but had higher misclassification rates, especially in classes with subtle color and texture differences, affirming that CNN was better suited for this classification task.

D. Accuracy vs Prediction Graph

An accuracy comparison graph was plotted to visually represent the performance of the CNN and Transformer models. The x-axis represented the model type, while they axis showed the achieved classification accuracy. CNN Model 3 scored an accuracy of 0.97, whereas the Vision Transformer reached 0.89.

This visual comparison clearly highlighted the superior performance of CNN in this specific application. The CNN’s ability to learn spatial hierarchies and localized features enabled it to outperform the Transformer, especially on a

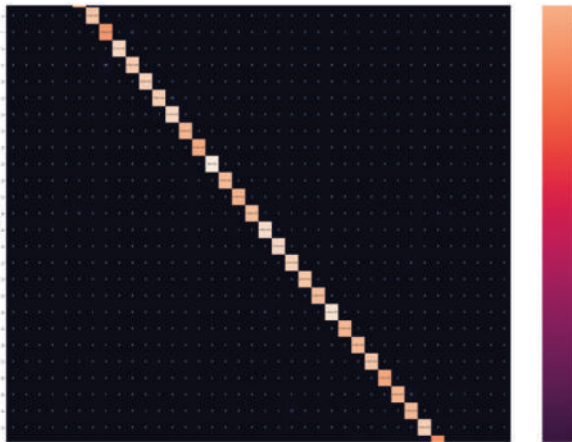


Fig. 3 Confusion matrix of CNN model

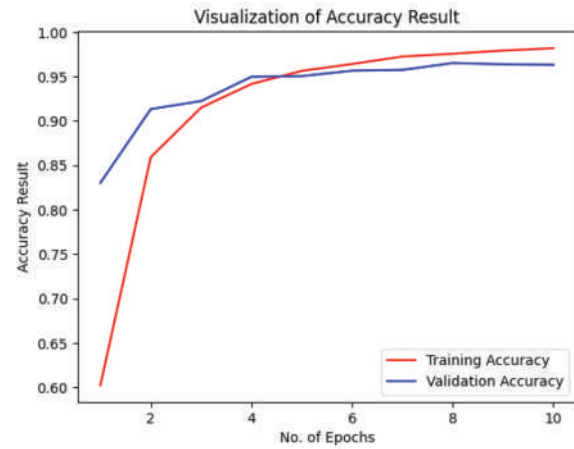


Fig. 6 Training vs validation accuracy of CNN model



Fig. 4 Confusion matrix of transformer model

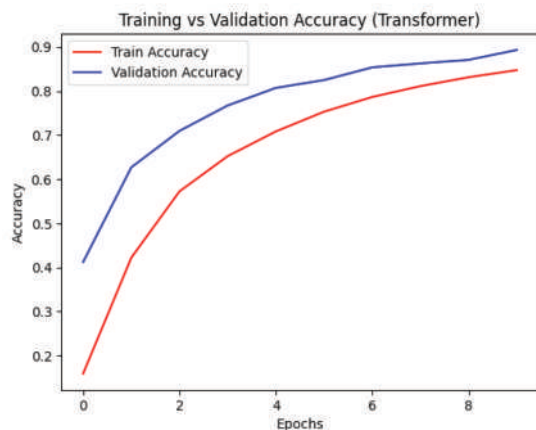


Fig. 5 Training vs validation accuracy of Transformer model

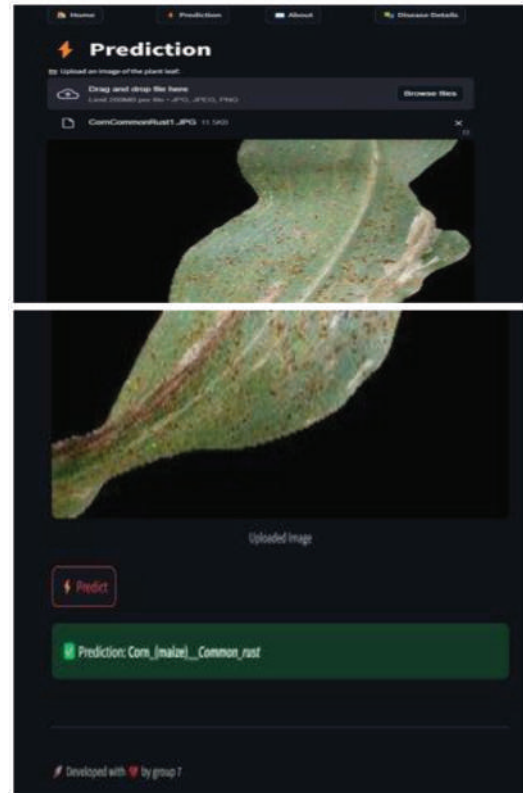


Fig. 7 Prediction page

moderately sized dataset like the one used in this study.

E. Web Application Deployment and Output

The best-performing CNN model (Model 3) was deployed as a real-time web application using Streamlit to ensure accessibility and usability for non-technical users. The system includes three core

interfaces. The homepage allows users to upload leaf images.

Upon submission, the prediction page displays the predicted disease class along with the confidence score returned by the model. The disease detail page provides descriptions, symptoms, and suggested remedies related to the predicted disease, making the system useful for farmers and agricultural professionals without technical knowledge.

V. Conclusion

The comparative study between Convolutional Neural Networks (CNN) and Vision Transformer (ViT) models for plant disease detection highlights clear differences in performance and practicality. Among the models, CNN Model 3 proved most effective, achieving 97% accuracy and an F1-score of 0.97, significantly outperforming the ViT model, which reached 89% accuracy.

CNN demonstrated strong generalization even with a moderate dataset, effectively capturing local features such as edges, textures, and leaf patterns—key for disease identification. Its lower computational complexity and faster training make it well-suited for real-time, resource-constrained environments.

In contrast, the ViT model showed potential in learning global patterns through self-attention but required larger datasets and longer training to match CNN performance, limiting its practicality in this context.

Evaluation through confusion matrices and application outputs further confirmed the robustness of CNN Model 3. Its integration into a Streamlit-based web application enables easy image input and instant disease prediction, making it useful for farmers and agricultural practitioners.

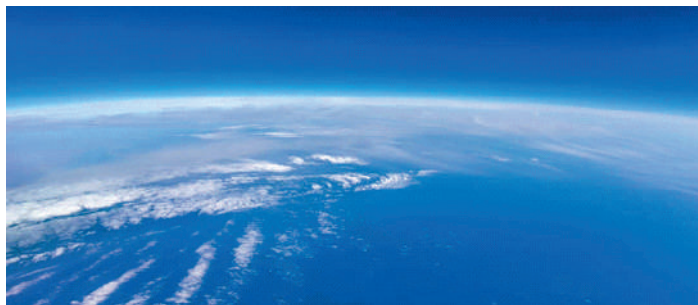
Overall, the CNN-based system offers high accuracy, efficiency, and practical usability, making it a reliable and scalable solution for early plant disease detection.

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Atmospheric Hydrogen is rising, which may be a problem for the Climate



Ice core records of atmospheric hydrogen reveal a significant rise in its concentration since the Industrial Revolution, which has contributed to global warming, indirectly by extending the atmospheric lifetime of methane.

Levels of hydrogen in the atmosphere have jumped by 60 per cent since pre-industrial times, underscoring the dramatic impact fossil fuel burning has had on the planet's atmospheric composition. Although hydrogen is not a greenhouse gas, it has an indirect warming effect through reactions with hydroxyl radicals.

Source: <https://www.newscientist.com/>

Nithin Kamath



In the world of current businesses, success is usually measured by how quickly they grow, how much venture capital they get, and how much hype they get all the time. Zerodha is an unusual yet very exciting business story in this context. Nithin Kamath started Zerodha in 2010. Traditional business practices prioritize sustainability, simplicity, and long-term thinking over rapid development.

Nithin Kamath is different from other startup leaders in India since he isn't loud or showy. A lot of entrepreneurship these days is about venture capital, fast growth, and continual attention. Kamath has followed a quieter and more thoughtful approach. He takes his time while creating a firm and focuses on long-term value instead of short-term excitement. He didn't start off as a normal founder. Kamath started out as a trader, learning the ins and outs of financial markets from the ground up. That early hands-on experience changed how he thought about investing. He didn't think it was just for a few people; he thought everyone should be able to understand it and access it. He didn't try to grow quickly or get money from outside sources. Instead, he concentrated on solving actual problems that regular investors face. This way of thinking eventually affected everything he built.

One of Kamath's most important decisions was to keep his business self-funded. He didn't take venture

financing, which provided him the opportunity to make choices based on his values instead of pressure. This independence let him focus on topics that typically get put on hold when trying to grow. Those are moral ways of doing business, building trust with customers, and caring for staff.

One thing that makes him different is that he is open about his mental health and burnout. Kamath has talked frankly about the emotional toll of starting a business in a world where success is sometimes seen as a requirement. He defies the mold of what a leader should be by being open and honest, and he promotes a better, more balanced view of what success actually is. He doesn't just work in business. Kamath has put time and money toward projects like Rainmatter that teach people about money, help the environment, and fight climate change. These projects show that he thinks that being an entrepreneur should help society, not merely make money.

Nithin Kamath's story is a welcome change from the conventional story of startup success. It shows that you don't need to be fast, loud, or always getting praise to construct something important. Sometimes the best way to make a lasting difference is to be clear, hold back, and have a strong sense of purpose.

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QoS-Aware Resource Management Techniques in Dynamic Cloud Milieu

The Cloud users hire resources from the Cloud datacenters to run their applications. Resources are allocated to the users in the form of logical entities called Virtual Machines (VMs). The VMs are placed on the physical machines or the servers of the datacenters. Hence, searching for an appropriate server from the datacenters to place the VM is a cumbersome process. This process is termed virtual machine placement (VMP). After resource allocation to the VMs, the users can utilize them to execute their tasks. The way in which the tasks are allocated to the VMs for execution is called as task scheduling. When the process of task scheduling is over, there may be cases where some VMs may be overutilized, leaving others in an underutilized state. Hence, load balancing among the VMs is carried out for better throughput. This cycle in Cloud computing, starting from resource allocation till task execution, is covered here in this thesis in a bottom up approach.

The problem of allocating resources to the VMs, scheduling tasks onto the VMs, and finally maintaining balance among the VMs are NP-hard problems. Normal heuristics are not capable of solving these problems. Hence, we have employed the metaheuristic techniques to find optimum solutions to these problems in Cloud milieu. We have chosen the most recent metaheuristic technique based on the swarming behaviour of the salps in the deep ocean, as it is simple and easy to implement with one main controlling parameter, yet robust in solving the optimization problems.

We have implemented the Salp Swarm algorithm with modifications and incorporation of requisite codes at each stage of our work for load balancing, task scheduling, and virtual machine placement to contribute a little towards the greater needs in Cloud domain. We have reconfigured the original Salp Swarm algorithm to make it self-adaptive to deal with the huge population of tasks and VMs for proper load balancing. Similarly, due to the chaotic nature of incoming tasks to the datacenters, we have implemented a chaotic map in Salp Swarm optimization to schedule the tasks efficiently onto the VMs. We have also incorporated the fault-tolerant mechanism into our task scheduling proposal. We have hybridized the Emperor Penguins Colony algorithm with the Salp Swarm optimization technique for effective VMP in the servers of the Cloud datacenters with the objective of minimizing the energy consumption in the Cloud milieu. We have further improvised the hybrid algorithm for VMP mentioned above on the basis of priority while considering the Cloud regions, availability zones, and the datacenters as a whole from the practical point of view. We have also worked on making the VMP energy efficient with the consideration of different aspects of energy consumption, with maximum use of green energy sources to minimize carbon emission while maintaining the response time and SLA violations satisfactorily. Our investigation on these multifaceted aspects of Cloud environment are found to be distinct and novel as compared to the existing ones.

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Signal Processing Techniques for Spaceborne Synthetic Aperture Radar (SAR)

Abstract

Spaceborne Synthetic Aperture Radar (SAR) has emerged as one of the most powerful remote sensing technologies for Earth observation, owing to its ability to operate independently of daylight and weather conditions. Central to SAR's performance is advanced signal processing, which enables the reconstruction of high-resolution images from coherently processed radar echoes. This article examines the core signal processing techniques employed in spaceborne SAR systems, including range and azimuth compression, Doppler processing, motion compensation, and speckle reduction. Emphasis is placed on the engineering challenges and algorithmic solutions that allow SAR to achieve fine spatial resolution from orbiting platforms.

Introduction

Unlike optical imaging systems, Synthetic Aperture Radar relies on microwave signals transmitted from a moving satellite platform toward the Earth's surface. The reflected echoes are recorded over time and processed coherently to synthesize a large antenna aperture, far exceeding the physical dimensions of the radar antenna itself. From an engineering standpoint, SAR is fundamentally a signal processing problem: weak, noise-corrupted echoes must be transformed into spatially accurate, high-resolution images. Fig. 1 illustrates a spaceborne SAR system [1], where a satellite transmits microwave signals toward the Earth and receives the reflected echoes to generate images. It

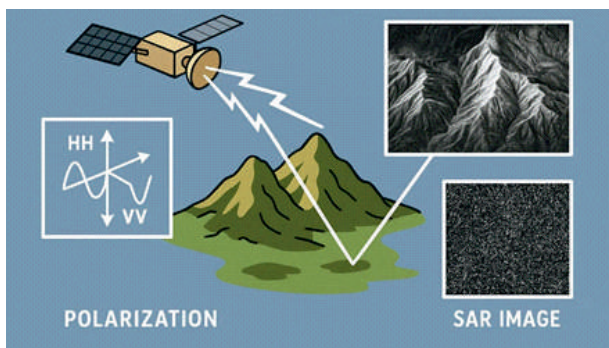


Fig. 1 Synthetic Aperture Radar (SAR)

also highlights polarization (HH, VV), which represents the orientation of transmitted and received waves used to capture different surface characteristics. The complexity of this task is amplified in spaceborne systems due to high orbital velocities, Doppler effects, platform motion errors, and stringent onboard computational constraints.

SAR Signal Model and Data Acquisition

A spaceborne Synthetic Aperture Radar (SAR) system transmits linearly frequency-modulated (chirped) pulses toward the Earth's surface, and the received signal is modeled as a time-delayed and Doppler-shifted version of the transmitted waveform, with its amplitude and phase determined by the radar cross-section of the target. In this process, range information is encoded in the time delay of the returned echoes, while azimuth information is captured through Doppler frequency variations caused by the motion of the satellite platform. Additionally, maintaining phase coherence is essential for successful aperture synthesis and high-resolution imaging. The collected SAR data is therefore organized as a two-dimensional matrix in range-azimuth space, which requires extensive signal processing before meaningful image formation can be achieved.

Range Compression

Range compression is the first major signal processing step in SAR image formation. It aims to improve range resolution by correlating the received echo with a replica of the transmitted chirp signal.

This is typically achieved using:

- Matched filtering in the time or frequency domain
- Fast Fourier Transform (FFT)-based convolution for computational efficiency

Mathematically, range compression maximizes the signal-to-noise ratio (SNR) while collapsing the extended chirp pulse into a narrow impulse response. The resulting improvement in range resolution is

critical for distinguishing closely spaced targets on the ground.

Azimuth Compression & Doppler Processing

Azimuth compression exploits the Doppler frequency history of each target as the satellite moves along its orbit, where a point target generates a characteristic Doppler chirp that is processed using azimuth matched filtering. This process involves key techniques such as Doppler centroid estimation, azimuth FFT processing, and synthetic aperture formation through coherent integration. Accurate azimuth compression enables SAR systems to achieve meter- or even sub-meter-scale resolution, despite having antennas that are only a few meters in length.

Motion Compensation

Spaceborne Synthetic Aperture Radar (SAR) systems assume a precisely known satellite trajectory; however, in practice, orbital perturbations, attitude variations, and platform vibrations introduce phase errors that degrade image quality. Motion compensation techniques address these issues by incorporating inertial navigation system (INS) and GPS data, applying phase correction algorithms during signal processing, and using autofocus methods when external motion data is insufficient. Without effective motion compensation, SAR images are prone to blurring and loss of coherence

Image Formation Algorithms

Several image formation algorithms are employed in spaceborne SAR systems depending on system geometry and performance requirements. The Range-Doppler Algorithm (RDA) is widely used due to its simplicity and computational efficiency, making it suitable for stripmap SAR applications. The Chirp Scaling Algorithm (CSA) improves processing speed and accuracy by eliminating interpolation steps. Meanwhile, the Omega-K ($\omega-k$) Algorithm, based on two-dimensional frequency-domain processing, provides high accuracy for wide-swath and high-resolution imaging scenarios. Each of these algorithms involves a trade-off between computational complexity, accuracy, and suitability for either onboard or ground-based processing.

Speckle Noise Reduction

A unique challenge in Synthetic Aperture Radar (SAR) imagery is speckle noise, which is a multiplicative noise caused by the coherent interference of scattered signals. To mitigate this effect, several speckle reduction techniques are employed, including adaptive spatial filters such as Lee, Frost, and Kuan filters, wavelet-based denoising methods, and multi-look processing approaches. In recent years, modern research has increasingly focused on deep learning-based despeckling techniques, which are more effective in preserving important image features such as edges and textures compared to traditional filtering methods.

Advanced & Emerging Techniques

Recent advancements in Synthetic Aperture Radar (SAR) signal processing include Polarimetric SAR (PolSAR) for material classification, Interferometric SAR (InSAR) for topographic mapping and deformation analysis, compressed sensing techniques for reducing data volume, and machine learning-assisted methods for image formation and target detection. Together, these approaches are transforming SAR from a purely imaging tool into a comprehensive geophysical sensing platform.

Conclusion

Signal processing is the cornerstone of spaceborne Synthetic Aperture Radar systems. From matched filtering and Doppler processing to motion compensation and advanced image formation algorithms, each stage plays a vital role in extracting meaningful information from raw radar echoes. As satellite missions demand higher resolution, wider coverage, and near-real-time processing, innovations in signal processing, particularly those leveraging AI and high-performance computing, will continue to define the future of SAR technology.

Resources :

<https://www.earthdata.nasa.gov/learn/earth-observation-data-basics/sar>

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Deforestation and the Changing Carbon Balance of the Amazon Rainforest



The Amazon Rainforest, often referred to as the “Lungs of the Earth,” is facing a great threat from deforestation. It is the world's largest rainforest, spanning 6.9 million square kilometres and covering around 40% of the South American continent. It is half of the planet's remaining tropical forests and also one of the most biologically diverse ecosystems. It is home to about three million species of plants and animals, as well as one million indigenous people; due to deforestation, this vital ecosystem is disappearing. Unfortunately, deforestation is threatening the health and future of this important rainforest, along with its support for wildlife and services. Globally, we lose about 10 million hectares and clearing for agriculture and livestock farming, logging activities to produce materials like paper, palm oil, and soy production, as well as gold mining. The Amazon rainforest covers land across nine countries, including Colombia and Peru, but around 60% of it lies within Brazil. Despite efforts to protect forest land, legal

deforestation remains rampant, and approximately one-third of global tropical deforestation occurs in Brazil's Amazon rainforest, resulting in the loss of about 1.5 million hectares each year.

The Amazon rainforest is a natural carbon sink and provides one of the greatest services for the planet by absorbing and storing carbon dioxide from the atmosphere. Its ability to do so is crucial in our fight against the climate crisis. As a result of persistent deforestation and a sharp increase in wildfires, the Amazon has become a source of carbon emitting a greater amount of carbon dioxide than it absorbs. Forest fires produce three times more carbon than the forests can absorb, thus creating a negative loop. The forest emitted about a billion tonnes of carbon dioxide a year equal to the annual emissions released in Japan, the world's fifth-biggest polluter.

Source : <https://earth.org/amazon-rainforest->

Industrial Automation Using 5 DOF Smart Robotic Arm

Abstract – This research presents the development of a 5-degree of freedom robotic arm designed for precise object manipulation. The robotic arm, powered by an Arduino. It employs multiple servo motors to control the base, shoulder, elbow, wrist, and gripper, ensuring a wide range of motion for efficient object handling. A key feature of this system is the integration of a color sensor, which detects the color of an object and facilitates automated sorting. Based on the detected color, the robotic arm autonomously picks up the object and places it in a designated area. Designed for applications in automation, education, and robotics research, this system demonstrates the feasibility of low-cost robotic automation with intelligent object sorting capabilities.

Keywords – Robotic arm, Arduino, Servo motors, Color sensor, Automated sorting, Industrial automation, Low-cost automation.

I. Introduction

In modern industrial environments, material handling and sorting are essential for ensuring production efficiency, consistency, and reduced labor dependency. Traditional manual methods of sorting are not only time-consuming but also prone to human error, especially in high-volume operations. To overcome these challenges, industries are increasingly integrating automation solutions into their workflows. Among these, robotic systems—especially robotic arms—have become central to smart manufacturing due to their capabilities in precision, repeatability, and continuous operation.

This work focuses on the development and implementation of a cost-effective, Arduino-based 5 Degrees of Freedom (DOF) robotic arm for automated object sorting based on color. The system utilizes a TCS3200 color sensor in conjunction with IR sensors and servo motors to identify, pick, and place objects into designated bins. Unlike high-end industrial robotic systems, this prototype is designed with affordability and accessibility in mind, making it suitable for educational, small-scale industrial, and research applications.

Numerous research efforts have explored similar robotic solutions, including color-based sorting arms and microcontroller-based manipulators. These studies validate the effectiveness of integrating servo actuators with low-cost sensors to automate sorting operations. However, most high-performance robotic arms remain financially out of reach for many small industries.

By leveraging open-source hardware platforms such as Arduino and using readily available sensors and actuators, this study provides an economical alternative while still maintaining functional robustness. Furthermore, the inclusion of a color sensor enables the robotic arm to classify objects dynamically, adding intelligence to the system without the complexity of advanced vision-based processing. This allows for significant improvements in accuracy and sorting efficiency compared to purely manual or static automated systems. In essence, this work not only demonstrates the feasibility of implementing an affordable robotic sorting solution but also highlights the growing potential of embedded systems and DIY robotics in transforming traditional industries into smart, automated environments.

II. Components

A. Arduino Uno

The Arduino Uno is an open-source microcontroller board based on the ATmega328P. It serves as the brain of the robotic arm system, processing input from sensors and controlling the output to servo motors. Its simplicity, cost-effectiveness, and strong community support make it ideal for embedded automation work like this one [1].

B. Color Sensor (TCS3200)

The TCS3200 is a programmable color light-to-frequency converter. It detects the RGB (Red, Green, Blue) values of objects and converts the light intensity into a frequency signal, which is then processed by the

Arduino to determine the object's color. This sensor enables the automated color-based sorting feature of the robotic arm.

C. IR Sensor

The Infrared (IR) sensors are used to detect the presence or absence of objects by emitting and receiving infrared light. In this system, they are employed to identify when an object arrives at the sorting station and when the output area is clear, helping in smooth transition between states in the automation process.

D. Servo Motors

The Servo motors are electromechanical devices used for precise control of angular position. In this study, five servo motors provide the robotic arm with five degrees of freedom, enabling complex movements such as base rotation, shoulder and elbow motion, wrist control, and gripper operation for picking and placing objects.

E. Power Supply

The power supply provides the necessary voltage and current to run the Arduino and all the connected servo motors. A stable and adequate power source is crucial for uninterrupted and smooth operation of the robotic arm, ensuring consistent servo response and sensor functionality.

F. Motor driver

A motor driver is an interface that allows a microcontroller to control motors by handling higher voltage and current. It enables direction and speed control, making it essential for operating the servo motors in robotic systems.

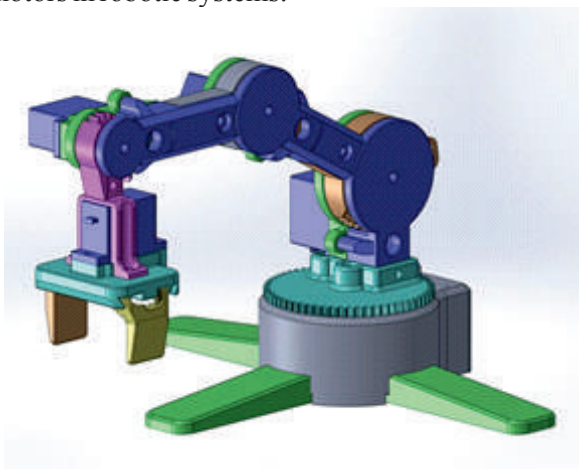


Fig. 1. 3D CAD Model of the 5-DOF Robotic Arm

G. Mechanical Frame

The mechanical frame forms the physical structure of the robotic arm. It holds all the components in place and ensures mechanical stability during operation. Lightweight yet sturdy materials are used to maintain balance between durability and ease of movement.

Breadboard

Connecting wires and a breadboard are used for assembling the electronic circuit of the system. They facilitate connections between the microcontroller, sensors, motors, and power supply, allowing for easy testing, debugging, and modifications during development.

III. Methodology

The methodology adopted for this research involves a systematic integration of hardware components and control logic to automate the color-based sorting process using a 5 DOF robotic arm as shown in Fig.1. The operation begins with the initialization phase, where all hardware elements—including servo motors, IR sensors, and the TCS3200 color sensor—are configured through the Arduino Uno microcontroller. The robotic arm is moved to a predefined home position to ensure consistency at startup [2].

Once initialized, the system enters a continuous loop governed by a finite state machine. In the `WAIT_FOR_INPUT` state, the input IR sensor checks for the presence of an object. Upon detection, the system transitions to `WAIT_FOR_OUTPUT_EMPTY`, where it ensures that the output area is unoccupied. If clear, the `PUSH_OBJECT` state moves the object under the color sensor using a slider mechanism.

The system then enters the `SAMPLE_COLOR` state, where multiple RGB readings are taken and averaged to accurately classify the object's color. The classification logic assigns the object as Red, Blue, Yellow, or Unknown. Based on this, the execute Pick And Place function is triggered, where the arm performs a sequence of pick, rotate, and place actions determined by predefined servo angles. After completion, the system resets to its idle state, waiting for the next cycle, and continues the process indefinitely for seamless automation.

III. System Design

The proposed system as shown in Fig. 2 is designed to automate the process of object sorting using a 5 Degrees of Freedom (DOF) robotic arm integrated with a microcontroller. The primary goal is to detect, identify, and sort objects based on their color using an Arduino Uno as the central control unit [3]. The system integrates an IR sensor to detect the presence of an object and a TCS3200 color sensor to classify the object's color. Once the color is identified, the Arduino processes the data and controls the servo motors to perform the appropriate pick-and-place operation. Table 1 shows the specifications of the robotic arm.

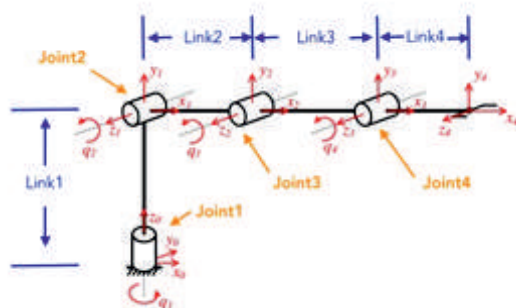


Fig. 2. Kinematic Diagram of a 5 DOF Articulated Manipulator

The robotic arm consists of five servo motors that enable movements at the base, shoulder, elbow, wrist, and gripper, providing multi-axis articulation for precise object handling. The gripper is responsible for securely grasping and releasing the object, while the base rotation allows the arm to position the object into its respective bin based on color classification.

The design ensures modularity and simplicity, making it adaptable for small-scale industrial tasks. Power is supplied externally, ensuring stable operation of both sensors and actuators. Overall, the system offers a compact and cost-effective solution for low-level industrial automation and demonstrates the practical application of embedded systems in robotics.

Table – 1 : Specifications of the designed robotic arm.

Specification	Number of the Axis	5 Axis
	Payload	50 g
	Power supply	110V/220V ,50/60 Hz
	Power in	5 V/5 A
Axis Movement	Axis	Range
	Joint 1 base	180°
	Joint 2 shoulder	180°

	Joint 3 arm	180°
	Joint 4 wrist	180°
	Joint 5 gripper	180°
Physical	Weight	300 g
	Dimension	250mm×200mm
	Materials	Plastic
	Controller	Arduino

IV. Results

This study presents the design and implementation of a low-cost, Arduino-based 5 Degrees of Freedom (DOF) robotic arm for industrial automation applications as shown in Fig. 3 to 7 . The system is capable of detecting, identifying, and sorting objects based on their color using a TCS3200 color sensor and IR sensor for presence detection.

The robotic arm, powered by multiple servo motors, mimics human-like movements for precise object handling. Controlled by an Arduino Uno microcontroller, the system operates autonomously by executing a sequence of pick-and-place operations. It efficiently classifies objects by color and deposits them into designated zones, reducing manual intervention and enhancing productivity. Emphasizing, affordability and ease of development, this work demonstrates the potential of embedded systems and robotics in automating repetitive industrial tasks. Its modular design and use of open-source hardware make it an excellent foundation for future improvements, such as machine vision integration or enhanced sorting logic.



Fig. 3 Sensing the colour of object



Fig. 4 Picking the object



Fig 5 Placing the object at designated area



Fig 6 Object sorted based on color and placed



Fig 7 Prototype of the 5 DOF Smart Robotic Arm

V. Conclusion and Future work

This work successfully demonstrates the design and implementation of a low-cost, Arduino-based 5 DOF smart robotic arm for automated color-based object sorting. By integrating sensors, servo motors, and an embedded control system, the robotic arm efficiently performs object detection, identification, and sorting with minimal human intervention. The system enhances operational accuracy, consistency, and

speed, making it suitable for repetitive industrial tasks.

The use of the TCS3200 color sensor enables reliable object classification, while IR sensors ensure effective presence detection, contributing to intelligent decision-making within the system. The coordinated control of multiple servo motors provides precise movement across all degrees of freedom, allowing smooth and accurate pick-and-place operations.

Furthermore, the proposed system highlights the potential of open-source platforms and affordable components in developing practical automation solutions. Its modular design allows for easy scalability and future enhancements, such as integration with machine vision systems, advanced control algorithms, or IoT-based monitoring.

In conclusion, this work serves as a cost-effective and efficient prototype for industrial automation, as well as a valuable educational tool for understanding robotics and embedded system design, aligning with the growing demand for smart manufacturing solutions.

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Venice: A 1600-year-old city resting on an upside-down forest!



The name Venice, Italy instantly conjures up images of canals, bridges and gondolas, with its stunning architecture, and a powerful maritime history. It is a UNESCO World Heritage site and a major global tourist destination, known for its romantic ambiance and rich cultural heritage.

Earlier on, in the very first episode of Historical Tidbits, we had expounded upon the ingenious wooden pile foundation that supports the Taj Mahal. An eerily similar yet much older version exists in the city of Venice, which is also 'founded' on wooden piles - logs mostly made of alder wood driven deep into the lagoon's clay, creating a solid base for stone structures. The piles compacted the soil, making a stable platform, upon which planks were laid in a cross-wise fashion to distribute the weight. The mineral-rich oxygen deficient saltwater also helped harden and preserve the wood. Subsequently Istrian stones were

placed on the wood, creating a robust, stable and water-resistant base, upon which buildings were constructed, allowing Venice to emerge from the water.

This ancient engineering feat, essentially an 'upside-down forest,' supports the entire city, allowing the iconic palazzi and canals to exist on the unstable lagoon - a true testament to medieval Venetian ingenuity.

Is the watery wooden pile foundation of the Taj Mahal and the city of Venice purely coincidental, or was there an early technology transfer? Pietra-Dura work, of Italian origin, is visible in the carvings of the Taj – just some food for thought!

(Content excerpted from Wikipedia and other web sources)

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