

Optimizing Pest Classification in Oil Palm Agriculture using Fine-Tuned GoogleNet Deep Learning Models

Umar Mulani¹, Dr. Vinod Ingale², Dr. Rais Mulla³, Ankita Aythankar⁴, Yogesh Mali⁵ and Vishal Borate⁶

^{1,2}Computer Engineering Department, K J College of Engineering and Management Research, Pune, India

Email: umar.mulani@gmail.com, vinod.ingale15@gmail.com

³Computer Engineering Department, Vasantdada Patil Pratishthan's College of Engineering & Visual Arts Soin, Mumbai.

Email: mtechraismulla@gmail.com

⁴Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, India

Email: ankita.avthankar@sitnagpur.siu.edu.in

⁵Department of AIML, G.H Raisoni College of Engineering and Management, Wagholi, Pune, India

Email: yogeshmali3350@gmail.com

⁶Department of Computer Engineering, Dr. D. Y. Patil College of Engineering and Innovation, Varale, Talegaon Dabhade, Pune, India

Email: vkborate88@gmail.com

Abstract—Recent developments in the field of deep learning models for agricultural pest classification, particularly in relation to oil palm cultivation, highlight the possibility of accurate and effective pest identification. The goal of this study is to use deep learning computation to classify pests in oil palm. The main goal is to evaluate this method's effectiveness in identifying pests. The GoogleNet architecture, GoogleNet with fine-tuned grid search, and GoogleNet with fine-tuned random search are all used in the study. A thorough examination of the performance of the three models is carried out using a variety of assessment metrics, including accuracy, precision, recall, and F1-Score. Photographs of pests on oil palm plants are included in the dataset. While models improved by grid search and random search show significant performance improvement, approaching nearly perfect evaluation metrics, the default GoogleNet model exhibits high accuracy. These results imply that customization improves the model's precision and effectiveness. The study's findings highlight the efficiency of GoogleNet -based models in oil palm farms for classifying pests, with fine-tuning considerably improving their output. In order to advance pest monitoring and management in oil palm cultivation, future research avenues should prioritize dataset expansion, additional model optimization, and the integration of drone-based automatic control and Internet of Things (IoT) technologies.

Index Terms— Classification; GoogleNet; Grid Search; Random Search, Pets Oil Palm.

I. INTRODUCTION

Favorable circumstances are found for oil palm, a growing agricultural crop, in tropical nations including Thailand, Papua New Guinea, Malaysia, and Indonesia [3]. Attacks by insects on oil palms are especially dangerous since they can stunt plant growth and reduce yield. In a larger perspective, productivity losses from pest infestations alone could amount to as much as 70% and the cumulative harm could be as high as 100% when combined with disease attacks [4].

Pest detection is one of the biggest challenges in agricultural production, accounting for 20% of global crop losses every year [5], [6]. Nearly 400 million hectares of land were impacted by plant diseases and pests in China alone in 2021. For this reason, prompt and accurate identification of pests and diseases in crops is crucial to agricultural output. This affects crop yields in addition to advancing the agricultural industry as a whole and raising farmers' incomes [7]. Creating artificial intelligence models based on agricultural image processing is a very successful tactic. These models are useful for identifying pests and grouping them into different categories [8], which make it possible to respond and intervene against pests in agricultural more effectively. Thus, losses in agricultural productivity are reduced and pest detection effectiveness is improved [9].

II. RESEARCH METHODS

A. Research Framework

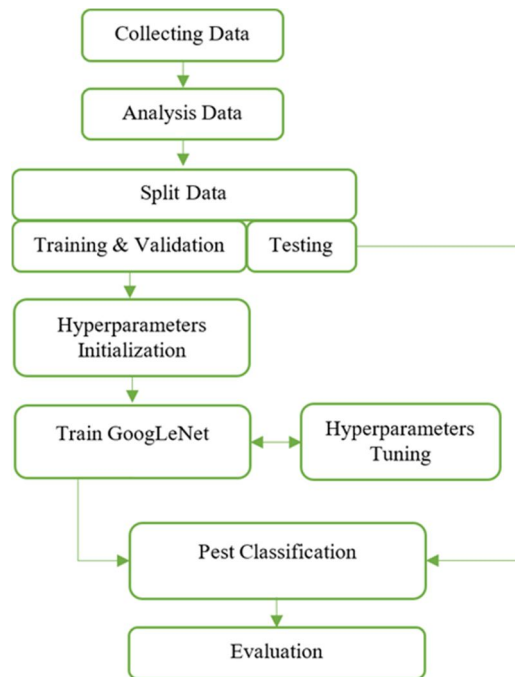


Figure 1. Confusion matrix (Top) GoogleNet (Middle) GoogleNet with Grid Search (Bottom) GoogleNet with Random Search

This study to categorize pests in oil palm plantations is shown in Figure 1 [11]. The first step in the research process is gathering data, which is then pre-processed to produce a dataset of appropriate and inappropriate photos that represent pest samples [12]. After that, the dataset is split up into three subsets: testing, validation, and training [13]. The training dataset is used to train the deep learning model, which makes use of the GoogleNet architecture [14]. After training, the validation dataset is used to evaluate the accuracy and performance of the model [15]. This includes calculating pertinent metrics like accuracy, precision, recall, and F1-score (Equations 1-4) [16]. In the end, testing the model on the independent testing set determines its effectiveness [17]. This all-encompassing method ensures that the developed pest classification model for oil palm plantations is reliable and robust [18].

B. Data collection and Pre-Processing data

Data on pests in the oil palm plantation of the Siantar Oil Palm Research Center were gathered for this study using a meticulous technical methodology [19]. The primary pests that are the subject of our research, *Metisaplana*, *Setoranitens*, and *Setothoseaasigna*, were depicted in the data as photographs [20]. Every bug was meticulously captured on camera to record its unique attributes [21]. We kept the shot distance between 15 and 20 cm in order to get precise and pertinent information [22].

One of the primary pests, *Metisaplana*, is distinguished by its unique patterned wings and body color, which frequently alternates between brown and green [23]. On the other hand, *Setoranitens* has a unique morphology, with longer wings and more vibrant body colors [24]. The primary distinguishing feature of *Setothoseaasigna* is its transparent wings with distinct pattern marks [25]. The methodical and comprehensive shooting procedure

results in very accurate data that is pertinent to our study goals on the oil palm farm [26].

Important measures are made to preserve the quality of the data that is ready for use during the data preparation stage [27]. Data cleaning is the first step in preparing the subject data, which involves finding and fixing any noise or anomalies that may exist in the dataset [28]. Before starting the analysis, this stage tries to guarantee the data's integrity [29]. After that, the image data is processed by resizing the pictures to uniform sizes so that they can be processed further [30]. In the context of picture recognition or image analysis tasks, resizing guarantees that all images have the same proportions [31].

Finally, data augmentation techniques are applied to enhance the diversity of the image dataset [32]. Operations like rotation, shearing, zooming, width shift, height shift, and vertical flip are examples of data augmentation [33]. As a result, the training data varies, which can aid machine learning models in comprehending various image variations that they might come across in the real world [1]. In image recognition and processing, data augmentation is a very helpful technique that can enhance model performance and avoid overfitting. Once the cleaning, resizing, and augmentation processes are combined, the data is prepared for additional analysis or deep learning model training [2].

C. Split Data

The dataset has 3000 photos divided into three pest categories, each comprising 1000 images, in order to prepare the data for analysis and training of the GoogleNet deep learning network. *Setora nitens*, *Setothosea asigna*, and *Metisa plana* are some of these classifications. After that, this dataset was split up into three different sets. The training data is the first set and is used to train the model so that it can recognize patterns in the data. The validation data, which makes up the second set, is used to assess how well the model performs during training, choose the ideal parameters, and avoid overfitting. In order to test the trained model with data that has never been seen before, the third batch of data is called test data. This allows for a more precise estimation of how much the model can be applied to real-world data. Before being employed in real-world applications, the 80:10:10 split guarantees that models are thoroughly tested, impartially assessed, and trained using an adequate amount of datasets.

D. Performance Measure

An effective method for evaluating an object estimation model's accuracy is the confusion matrix. It provides a thorough understanding of the model's performance by contrasting the predicted classification results with the actual class labels. The degree to which the model's predictions match the actual values is indicated by this method's accuracy. On the other hand, precision measures the accuracy of a prediction or its proportion. The model's recall quantifies its capacity to recognize accurate affirmative answers. Combining recall and precision yields the f1-score, which offer a fair and comprehensive evaluation performance of the model. The following formulas can be used to compute these metrics, where TP, TN, FP, and FN stand for true positive, false negative, false positive, and false negative, respectively.

E. Fine-tune GoogleNet Framework

Fine-tuning the selected GoogleNet model to optimize its performance in the context of palm oil pest classification was achieved through meticulous parameter adjustments. Employing grid search and random search techniques, The hyperparameters and their values that will be used in the tuning process are Epoch {10, 20 30}, Batch Size {16, 32, 64}, Learning Rate {0.001, 0.01, 0.1, 0.2, 0.3} and Optimizer {SGD, RMSProp, Adagrad, Adadelta, Adam, Adamax, Nadam} to determine the most effective combination. Through a comprehensive evaluation using grid search, we scrutinized each predefined parameter set in `param_grid`. Subsequently, with random search, we conducted experiments using diverse parameter combinations. These dual parameter search methodologies allowed us to pinpoint the optimal parameters, resulting in a model that demonstrated superior accuracy in identifying pests in oil palm.

TABLE II. NOTE HOW TABLE IS LEFT ALIGNED

Sample	Inception Voltage kV	Extinction Voltage kV
Pure Enamel	4.34	3.1
1:3 micro	5.15	4.2
3:1 micro	5.02	4
1:1 micro	4.91	3.8
1:3 nano	5.42	4.2
3:1 nano	5.32	4.1
1:1 nano	5.12	3.9

III. RESULT & DISCUSSION

A. Oil Palm Pest Samples

Three major pest species *Metisa plana*, *Setora nitens*, and *Setothosea asigna* are included in the sample data of pests on oil palm plants in this study. This dataset includes a range of photos that depict different field conditions and circumstances.



Figure 2. Oil Palm Pest (Top) *Metisa plana* (Middle) *Setora nitens* (Bottom) *Setothosea asigna*

B. Training GoogleNet

We ran the GoogleNet model on our preprocessed dataset in order to train it for pest classification on oil palms. Three different pest types on oil palms were identified using GoogleNet, which is well-known for its efficiency in image classification tasks: *Metisa plana*, *Setora nitens*, and *Setothosea asigna*. Using the Adam optimizer, the model was trained for 20 epochs with a batch size of 16. Over the course of the 20 epochs, the GoogleNet model's training results showed a noticeable improvement. On the training data, the model's accuracy was roughly 94.07% at first, and by the end of the training, it had increased to 99.46%. Interestingly, the model achieved 100% accuracy on the validation data in the final epochs, demonstrating its remarkable ability to identify pests on oil palm plants. On the other hand, possible overfitting should be avoided as it could jeopardize the model's ability to generalize to the validation data.

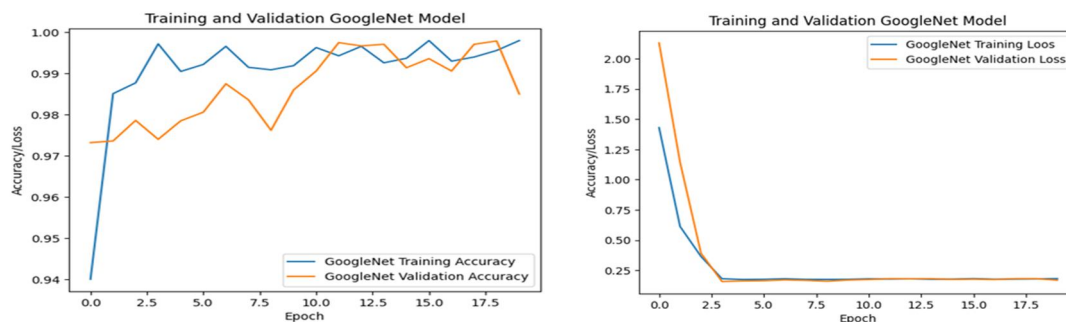


Figure 3. Training GoogleNet

C. Fine-Tuning GoogleNet with Grid Search

To get the best results, a number of experiments were carried out during the GoogleNet model's training phase using grid search for classifying pests on oil palms. The notable increase in model accuracy in these experiments can be attributed to the fine-tuning procedure. Grid search was used to investigate different parameter

combinations in an effort to determine which one would produce the best accuracy. The experimental findings highlight how crucial precise parameter tuning is to enhancing the GoogleNet model's capacity to recognize pests in oil palm plants. The results of using grid search to find the optimal hyperparameter are displayed in Table I.

TABLE I. BEST HYPERPARAMETER USING GRID SEARCH

Hyper parameter	Fine Tune Grid Search
Epochs & Batch Size	Best: 0.953433 using {'batch_size': 32, 'epochs': 50}
Optimizer	Best: 0.968667 using {'optimizer': 'Adam'}
Learning Rate	Best: 0.9500 using {'optimizer_learning_rate': 0.001}

Over the 30 training epochs, the trained model demonstrated remarkable advancement. The model started training with an accuracy of roughly 66.47% on the training set, and it got better and better until the end of training, when it was about 100% accurate. One noteworthy accomplishment is that in the last few epochs, the model was able to achieve perfect accuracy (100%) on the validation data. This shows how accurately the model can classify images related to pests on oil palm plants. This model's training is classified as good fitting since it can effectively generalize the patterns in the training and validation data due to its high degree of accuracy.

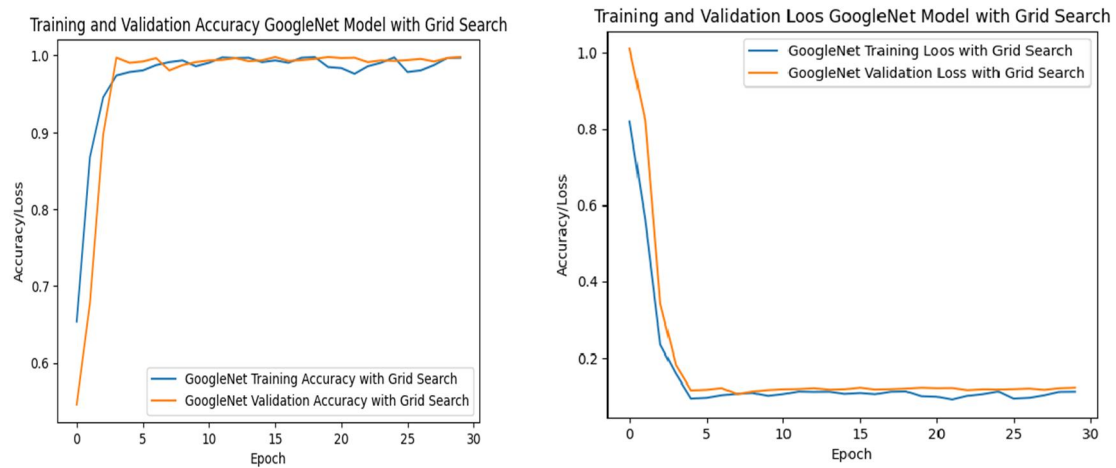


Figure 4. Training GoogleNet with Grid Search

D. Fine-Tuning GoogleNet with Random Search

To get the best results, a number of experiments were carried out during the training phase of the GoogleNet model with random search for classifying pests in oil palms. The notable increase in model accuracy in these experiments can be attributed to the fine-tuning procedure. Through random search, different parameter combinations were investigated in order to determine which one could produce the highest accuracy. The outcomes of the experiment highlight how crucial precise parameter tuning is to enhancing the GoogleNet model's capacity to recognize pests in oil palm plants. Table II displays the outcomes of using random search to identify the optimal hyperparameter.

TABLE II. BEST HYPERPARAMETER USING RANDOM SEARCH

Hyperparameter	Fine Tune Grid Search
Epochs & Batch Size	Best: {'epochs': 30, 'batch_size': 64}
Optimizer	Best: {'optimizer': 'SGD'}
Learning Rate	Best: {'optimizer_learning_rate': 0.001}

Over the 30 training epochs, the trained model demonstrated remarkable advancement. The model started training with an accuracy of roughly 77.92% on the training set, and it got better over time, finishing with an accuracy of roughly 99.71%. One noteworthy accomplishment is that in the last few epochs, the model was able to achieve perfect accuracy (100%) on the validation data. This shows how accurately the model can classify images related to pests on oil palm plants. This model's training is classified as good fitting since it can effectively generalize the patterns in the training and validation data due to its high degree of accuracy.

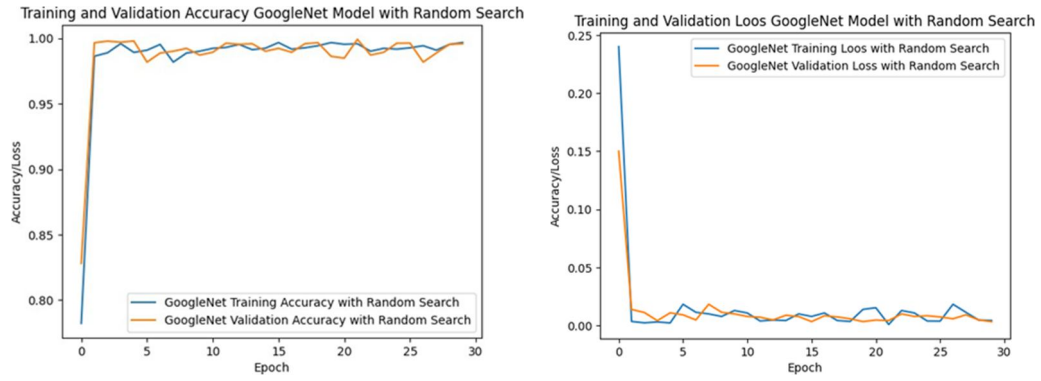


Figure 5. Training GoogleNet with Random Search

E. Evaluation

The evaluation phase includes a thorough examination of the GoogleNet -based models that have been developed, providing insight into how well they perform in the task of classifying pests in oil palm plants. A variety of metrics, such as accuracy, precision, and recall, are used in the thorough evaluation to provide a detailed picture of the models' performance in the assigned task. This assessment is essential to determining each model's effectiveness. A direct comparison between the GoogleNet model, the improved model via grid search, and the optimized model using a random search strategy is carried out. The debate that follows explores whether fine-tuning produces appreciable gains in model performance and determines which model is best suited for classifying pests in oil palms. Figures 6 visually represent the classification results for the three pest categories (Metisa plana, Setora nitens, and Setothosea asigna) using the three GoogleNet training models. The performance metrics and confusion matrix analysis provide insightful information that can be used to improve the model and get better classification results.

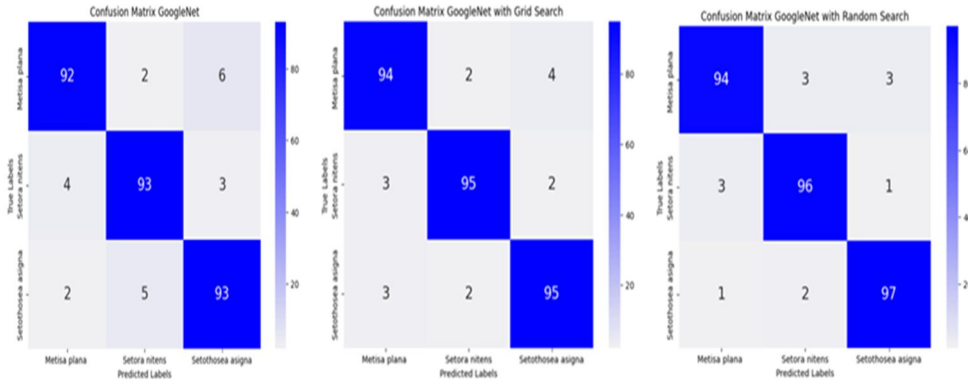


Figure 6. Confusion matrix (Top) GoogleNet (Middle) GoogleNet with Grid Search (Bottom) GoogleNet with Random Search

TABLE III. PERFORMANCE OF GOOGLNET FOR PALM OIL PEST CLASSIFICATION FOR SAMPLE 1

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9388	0.9200	0.9293	100
Setora nitens	0.9300	0.9300	0.9300	100
Setothosea asigna	0.9118	0.9300	0.9208	100
Accuracy	0.9267			300
Macro Average	0.9268	0.9267	0.9267	300

TABLE IV. PERFORMANCE OF GOOGLNET FOR PALM OIL PEST CLASSIFICATION FOR SAMPLE 2

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9400	0.9400	0.9400	100
Setora nitens	0.9596	0.9500	0.9548	100
Setothosea asigna	0.9406	0.9500	0.9453	100
Accuracy	0.9467			300
Macro Average	0.9467	0.9467	0.9467	300

TABLE V. PERFORMANCE OF GOOGLNET FOR PALM OIL PEST CLASSIFICATION FOR SAMPLE 3

Class	Precision	Recall	F1-Score	Support
Metisa plana	0.9592	0.9400	0.9495	100
Setora nitens	0.9505	0.9600	0.9552	100
Setothosea asigna	0.9604	0.9700	0.9652	100
Accuracy	0.9567			300
Macro Average	0.9567	0.9567	0.9566	300

With great accuracy, the GoogleNet model classifies pests in oil palm. Evaluation metrics demonstrated strong performance, including precision, recall, and F1-Score. The model's precision for *Metisa plana* is approximately 93.88%, recall is approximately 92%, and F1-Score is approximately 92.93%. The F1-Score is approximately 93%, recall is approximately 93%, and precision is approximately 93% for *Setora nitens*. In contrast, *Setothosea asigna* has an approximate 92.08% F1-Score, a recall of 93%, and a precision of 91.18%.

F. Discussion

When it came to classifying pests on oil palms, the three models this study evaluated—the default GoogleNet, GoogleNet with resets using a grid search approach, and GoogleNet with resets using a random search approach—performed remarkably well. The GoogleNet model by default showed good precision, recall, and high accuracy. On the other hand, performance was significantly improved by fine-tuning using grid search and random search, with metric evaluations nearly perfect. The utilization of these two refinement techniques yielded an incredibly efficacious and precise GoogleNet model for pest identification in oil palm, indicating noteworthy prospects for augmenting pest observation and control methodologies in oil palm cultivation.

IV. CONCLUSION

The results of this study show that three evaluated models—the default GoogleNet, the GoogleNet with grid search fine-tuning, and the GoogleNet with random search fine-tuning perform remarkably well in the classification of pests in oil palm. The GoogleNet model that was used by default produced excellent recall and precision at a high accuracy level. On the other hand, significant performance gains were achieved through fine-tuning using grid search and random search, nearly reaching perfection in metric evaluations. This study effectively used the GoogleNet model for oil palm pest identification when compared to related research. In order to improve accuracy and efficacy in monitoring and managing pests in oil palm, future research endeavors may take into account increasing the dataset size, further optimizing the model, and integrating drone-based automatic control technology and the Internet of Things (IoT).

REFERENCES

- [1] Chaudhari et al., "Cyber Security Challenges in Social Meta-verse and Mitigation Techniques," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSociCon), Pune, India, 2024, pp. 1-7, doi: 10.1109/MITADTSociCon60330.2024.10575295.
- [2] Modi, S., Mane, S., Mahadik, S., Kadam, R., Jambhale, R., Mahadik, S., & Mali, Y. (2024). Automated Attendance Monitoring System for Cattle through CCTV. REDVET-Revista electrónica de Veterinaria, 25(1), 2024.
- [3] Bhongade, A., Dargad, S., Dixit, A., Mali, Y.K., Kumari, B., Shende, A. (2024). Cyber Threats in Social Metaverse and Mitigation Techniques. In: Somani, A.K., Mundra, A., Gupta, R.K., Bhattacharya, S., Mazumdar, A.P. (eds) Smart Systems: Innovations in Computing. SSIC 2023. Smart Innovation, Systems and Technologies, vol 392. Springer, Singapore. https://doi.org/10.1007/978-981-97-3690-4_34.
- [4] S. P. Patil, S. Y. Zurange, A. A. Shinde, M. M. Jadhav, Y. K. Mali and V. Borate, "Upgrading Energy Productivity in Urban City Through Neural Support Vector Machine Learning for Smart Grids," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-5, doi: 10.1109/ICCCNT61001.2024.10724069.
- [5] S. Modi, M. Modi, V. Alone, A. Mohite, V. K. Borate and Y. K. Mali, "Smart shopping trolley Using Arduino UNO," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725524.
- [6] U. Mehta, S. Chougule, R. Mulla, V. Alone, V. K. Borate and Y. K. Mali, "Instant Messenger Forensic System," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10724367.
- [7] V. Ingale, B. Wankar, K. Jadhav, T. Adedjoja, V. K. Borate and Y. K. Mali, "Healthcare is being revolutionized by AI-powered solutions and technological integration for easily accessible and efficient medical care," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725646.

- [8] S. Sonawane, U. Mulani, D. S. Gaikwad, A. Gaur, V. K. Borate and Y. K. Mali, "Blockchain and Web3.0 based NFT Marketplace," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10724420.
- [9] P. Mandale, S. Modi, M. M. Jadhav, S. S. Khawate, V. K. Borate and Y. K. Mali, "Investigation of Different Techniques on Digital Actual Frameworks Toward Distributed Denial of Services Attack," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725776.
- [10] A. More, S. Khane, D. Jadhav, H. Sahoo and Y. K. Mali, "Auto-shield: Iot based OBD Application for Car Health Monitoring," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-10, doi: 10.1109/ICCCNT61001.2024.10726186.
- [11] U. H. Wanaskar, M. Dangore, D. Raut, R. Shirbhate, V. K. Borate and Y. K. Mali, "A Method for Re-identifying Subjects in Video Surveillance using Deep Neural Network Fusion," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-4, doi: 10.1109/ICCCNT61001.2024.10726255.
- [12] A. More, O. L. Ramishte, S. K. Shaikh, S. Shinde and Y. K. Mali, "Chain-Checkmate: Chess game using blockchain," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-7, doi: 10.1109/ICCCNT61001.2024.10725572.
- [13] A. O. Vaidya, M. Dangore, V. K. Borate, N. Raut, Y. K. Mali and A. Chaudhari, "Deep Fake Detection for Preventing Audio and Video Frauds Using Advanced Deep Learning Techniques," 2024 IEEE Recent Advances in Intelligent Computational Systems (RAICS), Kothamangalam, Kerala, India, 2024, pp. 1-6, doi: 10.1109/RAICS61201.2024.10689785.
- [14] J. D. Palkar, C. H. Jain, K. P. Kashinath, A. O. Vaidya, V. K. Borate and Y. K. Mali, "Machine Learning Approach for Human Brain Counselling," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-8, doi: 10.1109/ICCCNT61001.2024.10723852.
- [15] M. Dangore, S. Modi, S. Nalawade, U. Mehta, V. K. Borate and Y. K. Mali, "Revolutionizing Sport Education With AI," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-8, doi: 10.1109/ICCCNT61001.2024.10724009.
- [16] M. Dangore, D. Bhaturkar, K. M. Bhale, H. M. Jadhav, V. K. Borate and Y. K. Mali, "Applying Random Forest for IoT Systems in Industrial Environments," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-7, doi: 10.1109/ICCCNT61001.2024.10725751.
- [17] A. More, S. R. Shinde, P. M. Patil, D. S. Kane, Y. K. Mali and V. K. Borate, "Advancements in Early Detection of Lung Cancer using YOLOv7," 2024 5th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2024, pp. 1739-1746, doi: 10.1109/ICOSEC61587.2024.10722534.
- [18] Y. K. Mali, L. Sharma, K. Mahajan, F. Kazi, P. Kar and A. Bhogle, "Application of CNN Algorithm on X-Ray Images in COVID-19 Disease Prediction," 2023 IEEE International Carnahan Conference on Security Technology (ICCST), Pune, India, 2023, pp. 1-6, doi: 10.1109/ICCST59048.2023.10726852.
- [19] Y. K. Mali and A. Mohanpurkar, "Advanced pin entry method by resisting shoulder surfing attacks," 2015 International Conference on Information Processing (ICIP), Pune, India, 2015, pp. 37-42, doi: 10.1109/INFOP.2015.7489347.
- [20] Hrushikesh Kale, Kartik Aswar, Kisan Yadav, Dr. Yogesh Mali, "Attendance Marking using Face Detection", International Journal of Advanced Research in Science, Communication and Technology (IJARSCT) Volume 4, Issue 3, October 2024, pp 417-424 DOI: 10.48175/IJARSCT-19961.
- [21] Faizan Inamdar, Dev Ojha, Chaitanya Jakate, Dr. Yogesh Mali, "Job Title Predictor System", International Journal of Advanced Research in Science, Communication and Technology (IJARSCT) Volume 4, Issue 3, October 2024, pp 457-463 DOI: 10.48175/IJARSCT-19968.
- [22] Sawardekar, Sonali, Rahesha Mulla, Sonali Sonawane, Asharani Shinde, Vishal Borate, and Yogesh Kisan Mali. "Application of Modern Tools in Web 3.0." In Proceedings of Third International Conference on Computational Electronics for Wireless Communications: ICCWC 2023, Volume 2, p. 0. Springer Nature.
- [23] Y. Mali and V Chapte, "Grid based authentication system", International Journal of Advance Research in Computer Science and Management Studies, vol. 2, no. 10, pp. 93-99, 2014.
- [24] Yogesh Mali and Tejal Upadhyay, "Fraud Detection in Online Content Mining Relies on the Random Forest Algorithm", SWB, vol. 1, no. 3, pp. 13–20, Jul. 2023, doi: 10.61925/SWB.2023.1302.
- [25] P. Shimpi, B. Balinge, T. Golait, S. Parthasarathi, C. J. Arunima and Y. Mali, "Job Crafter - The One-Stop Placement Portal," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-8, doi: 10.1109/ICCCNT61001.2024.10725010.
- [26] D. Sengupta, S. A. Nalawade, L. Sharma, M. S. J. Kakade, V. K. Borate and Y. K. Mali, "Enhancing File Security Using Hybrid Cryptography," 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-8, doi: 10.1109/ICCCNT61001.2024.10724120sease Identification System." (2019).
- [27] Gayatri Hogale, Kalyani Pawar, Sneha Jadhav, Soma Joshi, Dr. Yogesh Mali, "Video HR Interview Bot using Artificial Intelligence", International Journal of Advanced Research in Science, Communication and Technology (IJARSCT) Volume 4, Issue 5, November 2024, pp 259-268 DOI: 10.48175/IJARSCT-22442.

- [28] S. A. Nalawade, R. Pattnaik, S. Kadam, P. P. Lodha, Y. K. Mali and V. K. Borate, "Smart Contract System with Blockchain Capability for Improving Supply Chain Management," 2024 3rd International Conference for Advancement in Technology (ICONAT), GOA, India, 2024, pp. 1-7, doi: 10.1109/ICONAT61936.2024.10774955.
- [29] P. B. More, A. N. Jadhav, I. Khatik, S. Singh, V. K. Borate and Y. K. Mali, "Sign Language Recognition Using Hand Gestures," 2024 3rd International Conference for Advancement in Technology (ICONAT), GOA, India, 2024, pp. 1-5, doi: 10.1109/ICONAT61936.2024.10774685.
- [30] Yogesh Mali and NilaySawant, "Smart Helmet for Coal Mining", International Journal of Advanced Research in Science Communication and Technology, vol. 3, no. 1, February 2023.
- [31] Yogesh Mali and TejalUpadhyay, "Fraud Detection in Online Content Mining Relies on the Random Forest Algorithm", SWB, vol. 1, no. 3, pp. 13-20, Jul. 2023.
- [32] Y. Mali, M. E. Pawar, A. More, S. Shinde, V. Borate and R. Shirbhate, "Improved Pin Entry Method to Prevent Shoulder Surfing Attacks," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10306875.
- [33] V. Borate, Y. Mali, V. Suryawanshi, S. Singh, V. Dhole and A. Kulkarni, "IoT Based Self Alert Generating Coal Miner Safety Helmets," 2023 International Conference on Computational Intelligence, Networks and Security (ICCINS), Mylavaram, India, 2023, pp. 01-04, doi: 10.1109/ICCINS58907.2023.10450044.