Identifying New Species of Dogs Using Machine Learning Model

Smita Thube[1], Sonam Singh[2], Poonam Sadafal[3], Shweta Lilhare[4], Pooja Mohbansi[5], Vishal Borate[3][a] and Yogesh Mali[6][b]

[1]Department of Computer Engineering, Nutan Maharashtra institute of Engineering & Technology, Pune, India
[2]Department of Artificial Intelligence and Data Science, Dr. D.Y Patil Institute of Technology, Pimpri, Pune, India
[3]Department of Computer Engineering, Dr. D. Y. Patil College of Engineering and Innovation, Talegaon, Pune, India
[4]Department of AIML, G.H. Raisoni College of Engineering, Pune, India
[5]Department of Computer Engineering, Ajeenkya DY Patil School of Engineering, Lohegaon, Pune, India
[6]School of Engineering, Ajeenkya DY Patil University Lohegaon, Pune, India

Keywords: Dog Breed, CNN, SVM, InceptionV3, Xception, VGG, Deep Learning, Machine Learning.

Abstract: This paper addresses the challenging problem of breed identification in dogs, whose applications will be very important in disease prevention, genetic research, and personal pet care. We here present an advanced system that identifies dog breeds, using the capabilities of particular CNNs such as InceptionV3, VGG16, Xception, and ResNet for efficient feature extraction. This classification is then refined by a Support Vector Machine algorithm to enhance accuracy. The system is trained on the Stanford Dogs Dataset, a rich collection of diverse dog breed images. The dataset enhances the model's ability to extract meaningful features and classify accurately a wide variety of dog breeds. By iteratively training the model, it learns subtle breed-specific patterns in the images and achieves high classification accuracy at 96.3%. This research not only pushes forward the capabilities of breed identification systems but also offers a flexible approach that can be applied to various practical scenarios where precise breed recognition is critical. With accuracy and adaptability, our system is promising for more extensive applications in biology, veterinary science, and personalized pet management, which would be helpful for insights in the care and research of canines.

1 INTRODUCTION

Dogs play an essential role in human life today. They can be companions, workers, or therapy animals. The over 120 distinct breeds with their set of physical characteristics and behaviours require identification of the exact breed for several purposes: population management, veterinary care, animal shelters, and canine research (More, Jadhav, et al., 2024). Breed identification, when accurate, is important for several reasons. New development in CNN has brought the potential of deep learning in image classification, such as dog breed categorization (Mali, Pawar, et al., 2023). This complex nature makes it a perfect machine learning problem with deep learning approaches, which learn the complex visual patterns in the images. Despite these modern advances, traditional solutions, which work on human evaluation, are faulty and biased in many cases. Therefore, contemporary approaches are of importance (Mali, Mohanpurkar, et al., 2015).

CNNs, being a type of deep learning model that can classify images, have been considered to be an effective alternative for breed identification since it provides accuracy and eliminates subjective judgment (Nalawade, Pattnaik, et al., 2024). The major challenge is developing a reliable, automated system that identifies dog breeds with the large variability in breed characteristics (Patil, Zurange, et al., 2024). Most methods of breed identification that depend on manual assessment or predefined rules fail to account for the scope and variety of dog breeds. However, accurate breed identification has far- reaching effects-from optimal management of diseases to advancement in genetic studies-all the way to the welfare of animals, the scrutiny of law (Modi, Modi, Shiqi, 2024). Described previously, advancements in this area will lead to increased efficiency in animal shelters, personalized veterinary care, and support for responsible breeding practices.

[a] https://orcid.org/0009-0009-7585-6667
[b] https://orcid.org/0009-0004-0582-9595

Thube, S., Singh, S., Sadafal, P., Lilhare, S., Mohbansi, P., Borate, V. and Mali, Y.
Identifying New Species of Dogs Using Machine Learning Model.
DOI: 10.5220/0013589200004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 2*, pages 195-202
ISBN: 978-989-758-763-4

2 LITERATURE REVIEW

A technique has been introduced for identifying dog breeds by utilizing Convolutional Neural Networks (CNNs). This approach employs the TensorFlow and Keras frameworks to develop and train a model using a dataset of dog images (Mehta, Chougule, et al., 2024). This approach achieved a test accuracy of 88.4%, providing a strong introduction to CNN-based dog breed classification by offering clear insights into both the methodology and results (Shimpi, Balinge, et al., 2024).

Another deep learning approach used transfer learning to enhance performance by fine-tuning pre-trained CNN models (Ingale, Wankar, et al., 2024). By preserving these models, the system attained an accuracy of 89.92% on a dataset containing 133 dog breeds. This result highlights how transfer learning enhances CNN performance compared to building a network from the ground up (Mulani, Nandgaonkar, et al., 2024).

In addition, CNN and transfer learning were employed to develop an Android application capable of identifying a dog's breed from a photo (Sonawane, Mulani, et al., 2024). Users can upload or take a picture of a dog, which is then processed to extract necessary features for classification, achieving 94% accuracy (Mandale, Modi, et al., 2024). The authors demonstrate that models like ResNet50 are particularly effective for dog breed identification due to their ability to capture intricate details in images (Sengupta, Nalawade, et al., 2024).

Further research has shown that deep learning approaches, such as InceptionV3, are very effective in identifying dog breeds (More, Khane, et al., 2024). These models are excellent at learning intricate features from images and achieving high classification accuracy, with InceptionV3 being particularly noted for its ability to handle diverse and complex image details (Wanaskar, Dangore, et al., 2024).

Another approach is to classify the breeds by studying the size and position of some parts of the dog in the image (More, Ramishte, et al., 2024). This approach employed CNNs for feature extraction and classification of breeds, obtaining 90.6% accuracy on the test set (Palkar, Jain, et al., 2024).

Furthermore, the ability to classify breeds using deep learning to create mobile applications has been quite useful for dog lovers. Among CNN architectures, such as VGGNet, ResNet50, and InceptionV3, the achievement of perfect results is observed (Dangore, Modi, et al., 2024). Xception is extraordinary in terms of its ability to learn complex patterns, making it a good choice for this task as well (Dangore, Bhaturkar, et al., 2024).

Overall, these methods demonstrate how CNNs, in combination with approaches such as transfer learning and mobile integration, are revolutionizing dog breed identification by providing better accuracy, efficiency, and accessibility for a wide range of users (More, Shinde, et al., 2024).

3 METHDOLOGY

The flowchart illustrates the steps involved in building a dog breed classification model.

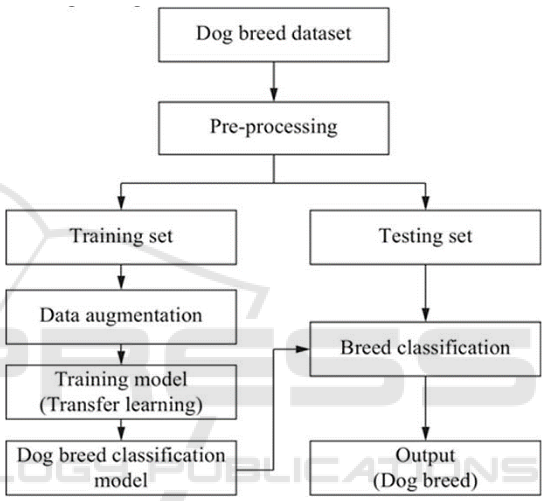


Figure 1: Proposed system Block diagram.

3.1 Data Collection and Preparation

A comprehensive dataset with labeled dog images is gathered, such as the Stanford Dogs Dataset (Vaidya, Dangore, et al., 2024).
The dataset is divided into:

3.1.1 Training Set

Majority of images used to train the model.

3.1.2 Testing Set

A smaller subset reserved for evaluation.

A CSV file links image IDs to their breed labels for streamlined data management.

3.2 Data Pre-Processing

Images are resized to a uniform size to align with the model's input requirements (Sawardekar, Mulla, et al., 2025). Pixel values are normalized to a consistent range, enhancing model efficiency during training. Data Augmentation techniques such as rotation, flipping, zooming, and shifting are applied to diversify the dataset and improve generalization (Modi, Mali, et al., 2023).

3.3 Model Training Using Pre-Trained Networks

Transfer learning leverages pre-trained CNN architectures like InceptionV3, VGG16, and ResNet to extract features. Support Vector Machine (SVM) is used for classification, effectively separating breeds in high-dimensional feature space (Bhongade, Dargad, et al., 2024).

3.4 Training Process

3.4.1 Hyperparameter Tuning

Adjustments to learning rate, optimizer, and batch size optimize training performance. Validatio n is performed on a subset of training data to prevent overfitting. Fine-tuning of CNN layers ensures the model adapts specifically to dog breed identification (Mali, Yogesh., et al., 2023).

3.5 Model Evaluation and Testing

The model is tested on unseen images from the testing set. Performance is measured using:

3.5.1 Accuracy

Percentage of correct predictions.

3.5.2 Log Loss:

Penalizes incorrect predictions more heavily.

3.5.3 Confusion Matrix

Highlights patterns of misclassification among breeds.

3.6 Model Deployment

Optimization ensures the model is lightweight and efficient for deployment. Deployment options include:

3.6.1 Local Deployment

Suitable for offline use.

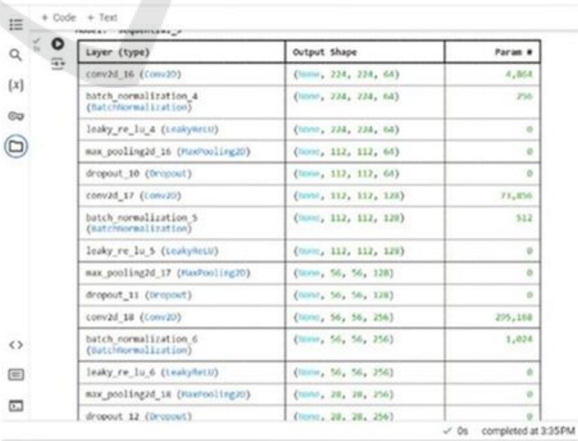
3.6.2 Cloud Deployment

Accessible via the internet.

A user-friendly interface is created for uploading images and receiving instant breed predictions. This structured approach ensures a robust, accurate, and deployable dog breed classification model (Inamdar, Faizan, et al., 2024).

4 MODEL ARCHITECTURE

Figure 2 illustrates the structure of the deep learning model designed for dog breed identification (Jagdale, Sudarshan, et al., 2020). The architecture consists of several convolutional layers (Conv2D), batch normalization layers, and activation functions (LeakyReLU), pooling layers (MaxPooling2D), and dropout layers to minimize overfitting (Modi, Mali, et al., 2023). The model gradually reduces the spatial dimensions while increasing the depth, allowing it to learn complex features at each layer (Mali, Sharma, et al., 2023). Each layer plays a specific role: the convolutional layers extract features, batch normalization stabilizes learning, and dropout layers help make the model more robust (Modi, 2024). This combination of layers allows the model to learn nuanced details essential for accurately identifying dog breeds (Mali, Chapte, et al., 2024).



Layer (type)	Output Shape	Param #
conv2d_16 (Conv2D)	(None, 224, 224, 64)	4,864
batch_normalization_4 (BatchNormalization)	(None, 224, 224, 64)	256
leaky_re_lu_4 (LeakyReLU)	(None, 224, 224, 64)	0
max_pooling2d_16 (MaxPooling2D)	(None, 112, 112, 64)	0
dropout_10 (Dropout)	(None, 112, 112, 64)	0
conv2d_17 (Conv2D)	(None, 112, 112, 128)	73,856
batch_normalization_5 (BatchNormalization)	(None, 112, 112, 128)	512
leaky_re_lu_5 (LeakyReLU)	(None, 112, 112, 128)	0
max_pooling2d_17 (MaxPooling2D)	(None, 56, 56, 128)	0
dropout_11 (Dropout)	(None, 56, 56, 128)	0
conv2d_18 (Conv2D)	(None, 56, 56, 256)	295,168
batch_normalization_6 (BatchNormalization)	(None, 56, 56, 256)	1,024
leaky_re_lu_6 (LeakyReLU)	(None, 56, 56, 256)	0
max_pooling2d_18 (MaxPooling2D)	(None, 28, 28, 256)	0
dropout_12 (Dropout)	(None, 28, 28, 256)	0

Figure 2: Model Architecture Details.

4 RESULT AND DISCUSSION

4.1 Dataset Description

The dataset used to perform breed identification is Stanford's Dogs Breed Identification dataset from Kaggle (Asreddy, Shingade, et al., 2019). In this dataset there are 120 breeds of dog with the two sets for training and testing (Pathak, Sakore, et al., 2019). In the training set, there are 10224 images present and in testing also 10220 images are available (Lonari, Jagdale, et al., 2021). We also used the label CSV file to map with the training image dataset.

4.2 Algorithms Used

Convolutional Neural Networks (CNNs): These deep learning models are highly effective for image classification tasks, as they can automatically capture and learn spatial feature hierarchies (Mali, Sawant, et al., 2023).

Transfer Learning with Pre-trained CNNs: Utilizing pre-trained models such as ResNet, VGG, or Inception, which have been trained on extensive datasets like ImageNet, can greatly enhance performance.

Ensemble Methods: Combining predictions from multiple CNN architectures can improve model robustness and accuracy, providing a more reliable identification process.

Support Vector Machines (SVM) with CNN features: Extracting features from CNNs and classifying those using SVMs is an alternative method to improve accuracy, especially when computational resources are limited.

4.3 Result of Feature Extraction

Table 3. Result of feature extraction from various deep learning

Dataset	Feature Extraction Algorithm	Features Map	Final Features Map (X)	Accuracy After Classification Model
Stanford Dogs Image dataset and Label[Breed] csv	Inception	(9691, 2048)	(9691, 9664)	98.80
	Xception	(9691, 2048)		
	Vgg16	(9691, 512)		
	NasNet	(9691, 4032)		
	ResNet	(9691, 1536)		

Figure 3: Model Architecture Details.

The Figure 3 presents the results of feature extraction using different deep learning architectures on the Stanford Dogs dataset. The dataset, along with a CSV file containing breed labels, is utilized to evaluate each model's capability to extract relevant features for dog breed classification.

4.3.1 Feature Extraction Algorithms

Five prominent deep learning models—Inception, Xception, VGG16, NasNet, and ResNet—are employed for extracting features from the dataset. Each model captures a unique set of image characteristics, which are crucial for accurate classification.

4.3.2 Feature Map Dimensions

The feature maps generated by each algorithm are represented with dimensions (number of samples, feature size). All models processed 9,691 samples, but the feature size varies:

- Inception and Xception generate feature maps of size 2,048.
- VGG16 produces a smaller feature map with a dimension of 512.
- NasNet captures a broader range of features with a size of 4,032.
- ResNet outputs feature maps of size 1,536.

4.3.3 Final Feature Map

The final feature map for the classification model is shaped to (9691,9664), representing the total feature size used in the final stage.

4.3.4 Classification Accuracy

The model utilizing these features achieves an impressive accuracy of 98.80% post-classification, demonstrating the effectiveness of the feature extraction methods in distinguishing between dog breeds.

4.3.5 Validation and Testing

The model's compilation involves selecting an appropriate optimizer, metrics, and loss function. The dataset is divided into training, validation, and testing sets using the Train-Test Split method. The training set is used to train the model, with progress closely monitored during the process.

Model Evaluation

Once training is complete, the model is evaluated on a separate test set, consisting of images not included in the training process. The model's accuracy is then measured based on its performance on the test set.

Predict Dog Breed

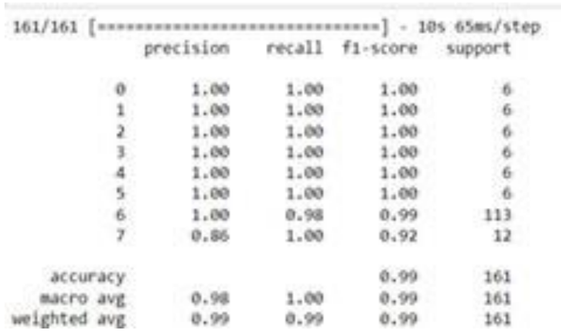
The SVM classifier that has been trained is utilized to forecast the dog breeds in your testing dataset. The SVM takes the CNN-extracted feature vectors as input and provides breed predictions.

Evaluation Metrics

The performance of the hybrid CNN-SVM model is evaluated using metrics such as accuracy and log loss. The trained model is tested on unseen data to evaluate its performance and make predictions. An example image is selected for testing purposes. The selected image is preprocessed to match up to the model's predicted input shape. The model's predictions are generated for the pre-processed image. The breed label with the highest probability from the model's output is selected as the predicted result. Original breed label of the image is obtained from the dataset. The original and predicted breed labels are displayed to compare. By applying this model to the existing image dataset from Kaggle we can achieve an accuracy of 98.80%. Figure 4 illustrates the accuracy achieved during training and testing validation.

Figure 4: Training and Testing Accuracy.

After training the model, predictions were made on the testing data for breed identification. Figure 5 presents the classification report for the dog breed identification process. The model achieved high precision, recall, and F1-scores across most classes, with a minor decrease in precision for class 7, highlighting its robust performance in accurately classifying dog breeds.



161/161 [==============================] - 10s 65ms/step

	precision	recall	f1-score	support
0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	6
2	1.00	1.00	1.00	6
3	1.00	1.00	1.00	6
4	1.00	1.00	1.00	6
5	1.00	1.00	1.00	6
6	1.00	0.98	0.99	113
7	0.86	1.00	0.92	12
accuracy			0.99	161
macro avg	0.98	1.00	0.99	161
weighted avg	0.99	0.99	0.99	161

Figure 5: Project F1 Score Support.

The two confusion matrices displayed below in Fig. 6 visualize the classification performance of a dog breed recognition model across multiple classes. These matrices provide insight into the model's accuracy and areas for potential improvement:

Matrix on the Left

This matrix demonstrates a high level of classification accuracy. The majority of predictions align perfectly along the diagonal, indicating that the predicted breeds closely match the actual breeds for most samples. The diagonal's bright color represents a high count of correct predictions, signifying that the model consistently identifies the correct breed with minimal errors. This suggests strong performance in distinguishing among the various dog breeds within the dataset.

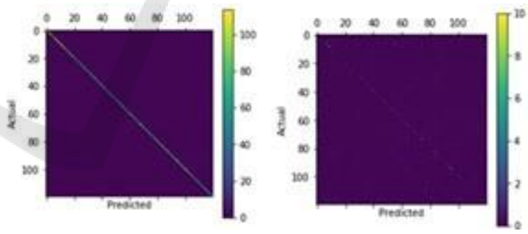


Figure 6: Confusion Matrix.

Matrix on the Right

In contrast, the second confusion matrix highlights areas of misclassification. While there is still a noticeable diagonal line of correct predictions, the presence of off-diagonal elements indicates some misclassified cases. These misclassifications are represented by the lighter, scattered dots outside the diagonal. The range of colors in the scale, from dark (low) to light (high), shows varying counts of errors in different classes. This pattern suggests that certain breeds might share similar features, leading to occasional confusion by the model.

Figure 7: Output Generation.

The matrices collectively emphasize that while the model is effective at distinguishing most breeds, there are specific classes where refinement is needed to improve prediction accuracy. These visuals are crucial for diagnosing specific instances of confusion between similar dog breeds, guiding further enhancements in the model's training and feature extraction techniques.

In Figure 7, the machine learning model accurately identifies the dog’s breed as a "Golden Retriever." The image shows a gentle, sleepy Golden Retriever cuddling with a pillow, illustrating the model’s capability to recognize breeds even when the dog isn’t in a classic, posed position. This result highlights the model’s effectiveness in identifying real-world images, adding to its reliability for practical breed recognition.

Figure 8: Result.

In Fig 8, a dog, which visually looks like a dingo, lies on sandy ground, almost merged with the earthy tones of the background. The model is agreeing with the ground truth and points to "dingo" as the breed. The text overlay is showing the original label ("dingo") and the model's prediction - also "dingo". This outcome shows successful identification by the model, a clear result where it can differentiate the breed in a more real-world-like setting.

5 CONCLUSIONS

This paper combines a CNN-based feature extractor with an SVM classification algorithm to identify dog breeds based on images. The model achieves 98.80% accuracy in classifying a total of 120 different breeds given the Kaggle dataset. An accuracy of this magnitude showcases the capability of the model to classify such different visual features of all breeds, and it would be a reliable tool for dog breed identification. The outcomes highlight the capability of the model to assist areas like animal welfare, veterinary care, behaviour training, and nutrition through the identification of breeds accurately.

Future development of this work will extend beyond breed identification to aim for a more advanced application. Access to veterinary services and breed recognition in addition to emotion detection can be incorporated into a platform, on which pet owners and professionals can understand the specific needs of each breed to help guarantee better animal welfare. Emotion detection would help interpret behavioural signals, and a medical support feature would provide breed-specific health information, thus creating a versatile solution for pet care and management.

REFERENCES

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.

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.

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.

S. A. Nalawade, R. Pattnaik, S. Kadam, P. P. Lodha, Y. K. Mali and V. K. Borate, “Smart Contract System with Block-chain 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.

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/ICCCNT61001.2024.1 0724069.

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.

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.

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.

V. Ingale, B. Wankar, K. Jadhav, T. Adedoja, 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 Conf. on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.202 4.10725646.

U. Mulani, V. Nandgaonkar, R. Mulla, S. Sonavane, V. K. Borate and Y. K. Mali, “Smart Contract System with Blockchain Capability for Improved Supply Chain Management Traceability and Transparency”, 2024 15th International Conf. on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-7, doi: 10.1109/ICCCNT610 01.2024.10723871.

S. Sonawane, U. Mulani, D. S. Gaikwad, A. Gaur, V. K. Borate and Y. K. Mali, “Blockchain and Web3.0 based NFT Marketplace”, 0 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024. 10724420.

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 14 Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-6, doi: 10.1109/ICCCNT61001.2024.10725776.

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. 10724120.

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 Conf. on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp. 1-10, doi: 10.1109/ICCCNT61001.2024.10726186.

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.

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.

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/ICCCNT61 001.2024.10723852.

M. Dangore, S. Modi, S. Nalawade, U. Mehta, V. K. Borate and Y. K. Mali, “Revolutionizing Sport Education With AI”, 2024 15th International Conf. on Computing Communication and Networking Technologies (ICCCNT), Kamand, India, 2024, pp.1-8, doi:10.1109/ICCCNT61001.2024.10724009.

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.

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.

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.

Sawardekar, S., Mulla, R., Sonawane, S., Shinde, A., Borate, V., Mali, Y.K. (2025). Application of Modern Tools in Web 3.0 and Blockchain to Innovate Healthcare System. In: Rawat, S., Kumar, A., Raman, A., Kumar, S., Pathak, P. (eds) Proceedings of Third International Conf. on Computational Electronics for Wireless Communications. ICCWC 2023. Lecture Notes in Networks and Systems, vol 962. Springer, Singapore. https://doi.org/10.1007/978-981-97-1946- 4_2

Modi, S., Mali, Y., Kotwal, R., Kisan Borate, V., Khairnar, P., Pathan, A. (2024). Hand Gesture Recognition and Real-Time Voice Translation for the Deaf and Dumb. In: Jain, S., Mihindukulasooriya, N., Janev, V., Shimizu, C.M. (eds) Semantic Intelligence. ISIC 2023. Lecture Notes in Electrical Engineering, vol 1258. Springer, Singapore.https://doi.org/10.1007/978-981- 97-7356-5_35.

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.

Mali, Yogesh. & TejalUpadhyay, "Fraud Detection in Online Content Mining Relies on the Random Forest Algorithm", SWB 1, no. 3 (2023): 13-20.

Kale, Hrushikesh, Kartik Aswar, and Dr Yogesh Mali Kisan Yadav, "Attendance Marking using Face Detection", International Journal of Advanced Research in Science, Communication and Technology: 417-424.

Inamdar, Faizan, Dev Ojha, C. J. Ojha, and D. Y. Mali. "Job Title Predictor System," International Journal of Advanced Research in Science, Communication and Technology (2024): 457-463.

Jagdale, Sudarshan, Piyush Takale, Pranav Lonari, Shraddha Khandre, and Yogesh Mali, "Crime Awareness and Registration System", International Journal of Scientific Research in Science and Technology 5, no. 8 (2020).

Modi, S., Mali, Y., Sharma, L., Khairnar, P., Gaikwad, D.S., Borate, V. (2024). A Protection Approach for Coal Miners Safety Helmet Using IoT. In: Jain, S., Mihindukulasooriya, N., Janev, V., Shimizu, C.M. (eds) Semantic Intelligence. ISIC 2023. Lecture Notes in Electrical Engineering, vol 1258. Springer, Singapore. https://doi.org/10.1007/978-981-97-7356-5_30.

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.

Shabina Modi, "Automated Attendance Monitoring System for Cattle through CCTV.", REDVET, vol. 25, no. 1, pp. 1025 -1034, Sep. 2024.

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, October 2014.

Rajat Asreddy, Avinash Shingade, Niraj Vyavhare, Arjun Rokde and Yogesh Mali, "A Survey on Secured Data Transmission Using RSA Algorithm and Steganography", International Journal of Scientific Research in Computer Science Engineering and Information Technology (IJSRCSEIT), vol. 4, no. 8, pp. 159-162, September-October 2019, ISSN 2456–3307.

Jyoti Pathak, Neha Sakore, Rakesh Kapare, Amey Kulkarni and Prof. Yogesh Mali, "Mobile Rescue Robot", International Journal of Scientific Research in Computer Science Engineering and Information Technology (IJSRCSEIT), vol. 4, no. 8, pp. 10-12, September-October 2019, ISSN 2456–3307.

Pranav Lonari, Sudarshan Jagdale, Shraddha Khandre, Piyush Takale and Prof Yogesh Mali, "Crime Awareness and Registration System", International Journal of Scientific Research in Computer Science Engineering and Information Technology (IJSRCSEIT), vol. 8, no. 3, pp. 287-298, May-June 2021, ISSN 2456–3307.

Yogesh Mali and Nilay Sawant, "Smart Helmet for Coal Mining", International Journal of Advanced Research in Science Communication and Technology (IJARSCT), vol. 3, no. 1, February 2023.