InfoTech Spectrum: Iraqi Journal of Data Science (IJDS)
ISSN: 3007-5467, Vol 2(No.1), 37-49 (2025)
DOI: https://doi.org/10.51173/ijds.v2i1.15
ijds.mtu.edu.iq

IMPACT OF COLOUR SPACE TRANSFORMATION ON SMOKE DETECTION ACCURACY USING RESNET50

Mohannad T. Mohammed [1*], Mohamed Safaa Shubber [2]

[1,2] *College of Health and Medical Techniques, Middle Technical University, 10047 Baghdad, Iraq.*

* *Corresponding author E-mail: mohannad.tm@mtu.edu.iq (Mohannad T. Mohammed)*

RESEARCH ARTICLE

ARTICLE INFORMATION

SUBMISSION HISTORY:

Received: 12 October 2024
Revised: 12 January 2025
Accepted: 22 January 2025
Published: 30 January 2025

KEYWORDS:

Colour Space Conversion;
CNN;
Deep Learning;
Early Fire Prevention;
Smoke Detection

ABSTRACT

Detecting smoke that precedes fire is a vital matter since it will detect fire incidents in a very early stage since these incidents have very high catastrophic effects on people's lives as well as industrial matters. In order to produce a more reliable detection system, in this article, we dove deeper to examine the effect of colour conversion of the captured footage to enhance the detection percentage using a pre-trained CNN model (ResNet50) that was altered to do a binary classification and was trained on a dataset that consists of smoke and non-smoke scenario images. We examined the system using the footage's original status (RGB) and also tested four colour spaces (HSV, YCbCr, LAB, and grayscale). The testing results showed that HSV had the highest accuracy of 92.1% and the lowest errors during training and testing. Regarding accuracy, the order after HSV was RGB, YCbCr, LAB, and finally, grayscale. Grayscale was the lowest in the testing results, with 85.4%. These results indicate that colour spaces do affect the detection quality and using them would improve the quality of smoke detection systems.

1. INTRODUCTION

Detection of early fire is critical for reducing fire's destructive effects on both humans and property[1]. Synthetic materials' increasing use in modern buildings that are high in flammability and promote fast fire propagation led to highlighting the demand for more sophisticated detection systems[2]. In the absence of early warning mechanisms, fires will quickly escalate, particularly in structures that contain these materials, which often release toxic gas and accelerate the fire spreading[3]. Old smoke detection systems which work on (ionization or photoelectric) principles have struggled in detecting early fire symptoms, such as smoke or slow-burning flames, that can potentially lead to a delay in responses[4]. Such limitations should concern environments where fires are not easy to detect. Also, it happens frequently, such as in industrial facilities, where early intervention is very vital to preventing damages and human and financial losses[5].

For years, old fire detection systems, such as the ones mentioned above, have been used extensively in areas like residential, commercial, and industrial places. Ionization detectors are adept at identifying fast flaming fires but are less effective at detecting them in time [6]. On the contrary, photoelectric detectors would perform better in detecting larger smoke from growing fires, although they may be slower to respond to flaming fires at their start[7].

Although they are widely adopted, both types of detectors have noticeable limitations, especially in areas that have high air circulation, open spaces, or places where early fire indicators, such as smoke, may scatter or go unnoticed[8]. The modern solutions involving AI (machine learning and computer vision) are presenting improvements regarding early smoke detection. Yet,

DOI: https://doi.org/10.51173/ijds.v2i1.15

they also have challenges related to computational costs, need extensive training data, and high rate of false positive rates[9]. These restrictions highlighted the need for continuing innovation in fire detection methods to enhance response times and reduce false positive alarms.

The primary aim of this research is to examine how colour space transformations[10] influence the accuracy of smoke detection using a deep learning model, specifically ResNet50[11]. Early smoke detection is crucial in preventing fires from spreading, enabling timely intervention to minimize damage to lives and property [12]. This study aims to focus on rating the various colour spaces' s impact on the model's accuracy in detecting smoke that precedes fire [13], stating the most effective of these colour spaces for smoke detection under multiple conditions, and shaping a methodology that could be considered robust for preprocessing, training and evaluating models. It also seeks to provide practical insights for improving real-world smoke detection systems, mostly in industrial and forest fire monitoring applications. Moreover, this research is aiming for future advancements, focusing on implementing the model on edge devices like smart cameras or drones and also expanding the dataset to include more varied environmental conditions such as lighting and weather conditions.

Regarding the contribution of this work, a comprehensive analysis is presented of how different colour space statuses may affect the performance of the smoke detection process. This study names the most effective colour space that can be used for early fire detection using machine learning techniques. These findings present a comprehension that will help in optimizing detection models, leading to the development of their reliability and evolving safety technologies.

1.1 Colour Spaces and Their Role in Smoke Detection

The colour space status of the captured images can have an undeniable effect on the performance of the smoke detection system, usually in situations where varying lighting conditions and image quality are presented [14]. As the colour space RGB (Red, Green and Blue) is considered the most commonly used format, alternative colour spaces exist, such as HSV, LAB, YCbCr and greyscale. These colour spaces grant a distinct advantage by splitting the brightness and other essential components of the image. HSV is known to enhance the detection of delicate colour variations in low-contrast conditions, which is necessary in the early stages of smoke detection [15]. Also, YCbCr and LAB, are both focusing on both chrominance and luminance differences, making them effective in detecting smoke in high density environments where shadows or other visual obstacles may interfere with detection[16]. As for Grayscale, it makes images simpler by reducing their intensity values, resulting in the elimination of colour information. In scenarios where the texture and shape are considered the primary indicators of smoke rather than colour information, the grey scale colour space will be the most appropriate choice[17]. These colour space conversions improve a model's capability to handle multiple scenes regarding the detection purpose, as colour information stands out more, leading to higher detection accuracy across various datasets [18][19]. Additionally, the use of multiple colour spaces allows for a better feature extraction process, which is essential for fine-tuning deep learning models such as ResNet50 in accurately detecting smoke in real-world conditions [20][21].

2. LITERATURE REVIEW

Researchers in [22] used (temporal and spatial) wavelet analysis in order to identify semi-transparent smoke using a static camera. This method is effective in self-controlled environments but may struggle in dynamic circumstances like the difference between day and night, highlighting the need for adaptive methods. A model utilizing illumination invariant colour descriptors for smoke detection was conducted in[23]. While promising, its reliance on handmade features confines it from generalization, highlighting the value of deep learning for automated feature extraction. The authors in [18] proposed a semantic separation technique for forest fire smoke that utilizes concentration weighting to moderate the smoke label ambiguity, lowering the separation performance due to smoke's transparency, unclear contours, and variable concentrations in supervised separation tasks. The technique established a mathematical correlation between smoke concentrations and their corresponding pixel values based on the principle that variable smoke attentions yield distinct pixel values in an image. The authors afterwards trained the model using together concentration weighting labels and basic labels, allowing the network to distinguish the unique significance of forest fire smoke pixels, hence justifying the impact of ambiguity rising from smoke data annotation on the smoke detection model. This approach improves accuracy but requires extensive manual annotation, suggesting a need for more scalable solutions.

Using a technique developed by [24], this vision sensor-based method facilitates smoke and flame detection in open and enclosed indoor and outdoor situations. Rule-based thresholding was utilized to figure out parameters such as turbulence, growth, and flow rate for discovering smoke and fire. Although efficient, fixed thresholds limit adaptability, favouring machine learning models that can dynamically adjust. Xu et al. proposed a deep domain-specific strategy that formed robust learned smoke detection features in films covering synthetic and real pictures. This method improves generalization but relies on large, labelled datasets, highlighting the need for techniques that work with limited data. The authors in [25] achieved improved separation outcomes by straight mixing features from RGB and depth images into their semantic separation model. While effective, the need for depth sensors adds cost and complexity, favouring RGB-only solutions. In contrast, the authors in [26] applied several colour space transformations on RGB fire images covering flame regions and joined the resultant features through a chain to enhance cataloguing efficacy. This demonstrates the potential of colour spaces but lacks exploration in deep learning contexts, a gap addressed in this study.

The research cited in [15] and [27] employed colour spaces (YUV and YCbCr, respectively) as colour metrics and integrated them through additional feature extraction procedures to recognize the smoke attendance in the video frames. These studies highlight the importance of Colour information but do not comprehensively compare multiple Colour spaces, a key contribution of this work. The quicker R-CNN model has been employed to recognize smoke in forest fires utilizing improved synthetic image data [28]. While accurate, its computational cost limits real-time applicability, emphasizing the need for efficient models like ResNet50. A fusion of the VGG16 and ResNet50 network strategies has been combined into a deep network to get better feature representation abilities while enhancing the general network complexity [20]. This improves performance but increases complexity, highlighting the importance of balancing efficiency and accuracy.

Recent instances of CNN models for smoke detection include temporal development and network mixtures, together with the two-stage training of a Deep Convolutional Generative Adversarial Network (DCGAN) [29], dilated CNN, deep saliency network, and deep dual-channel CNN solutions [30][31]. These methods show promise but are resource-intensive, underscoring the need for lightweight and practical solutions.

3. METHODS

Various deep-learning approaches have been utilized for fire and smoke detection; however, real-world conditions, such as varying lighting and environmental factors, can negatively impact their performance[32]. To address these challenges, this study focuses on the effectiveness of colour space transformations and employs the ResNet50 architecture for smoke detection. ResNet50 was selected due to its strong performance in image classification tasks[33]. Its residual learning framework mitigates the vanishing gradient problem, enabling the training of deep networks capable of capturing subtle visual features critical for smoke identification[11]. This study also explores colour space transformations by converting RGB images into alternative spaces since colour information plays a vital role in distinguishing smoke from other visual elements, mostly under varying lighting conditions.

Although other deep learning architectures, such as VGG16 and Inception, and other traditional methods like rule-based thresholding have been used for smoke detection[34], ResNet50 presents a balance between computational efficiency and accuracy. Alternate architectures were neglected due to their higher computation demands or lower interpretability, whereas ResNet50 provides a robust and efficient solution for this task. The methodology includes converting RGB images into multiple colour spaces (HSV, YCbCr, LAB, and Grayscale), followed by normalization[35].

The dataset was divided into training (70%), validation (15%), and test (15%) subsets using stratified sampling to ensure class balance[36]. A pre-trained ResNet50 model is adapted for binary smoke detection by modifying its architecture and training it with early stopping to prevent overfitting, As shown in Fig 1.

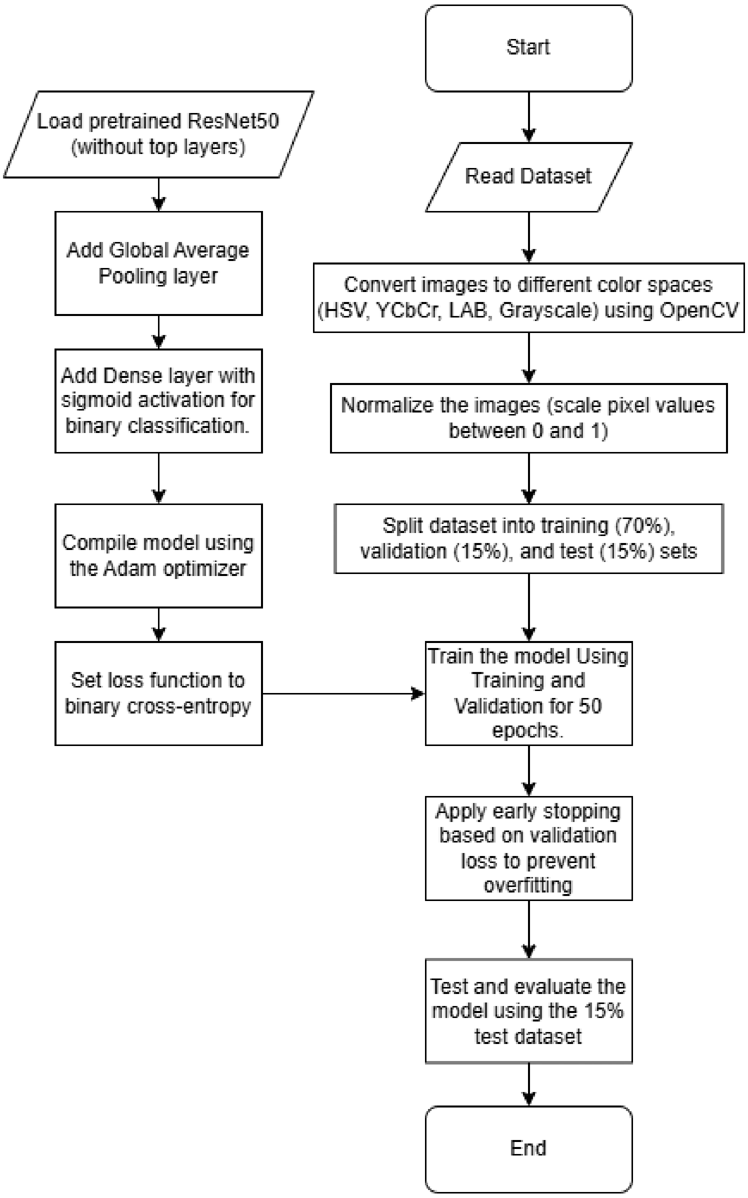

Figure 1: Proposed Framework

3.1 Data Collection

The "Smoke 100k" [37] presents a comprehensive dataset tailored for smoke detection. This dataset comprises 100,000 images, including those with smoke masks, smoke-free images, and annotated bounding box positions. Fig 2 shows an example of these images[38]. These annotations make the dataset valuable for training machine-learning models designed for smoke detection. To better simulate real-world conditions, the dataset was divided into three subsets categorized by complexity: low, medium, and high. Each subset contains synthesized smoke masks placed at different angles to imitate diverse smoke patterns, as shown in Table 1.

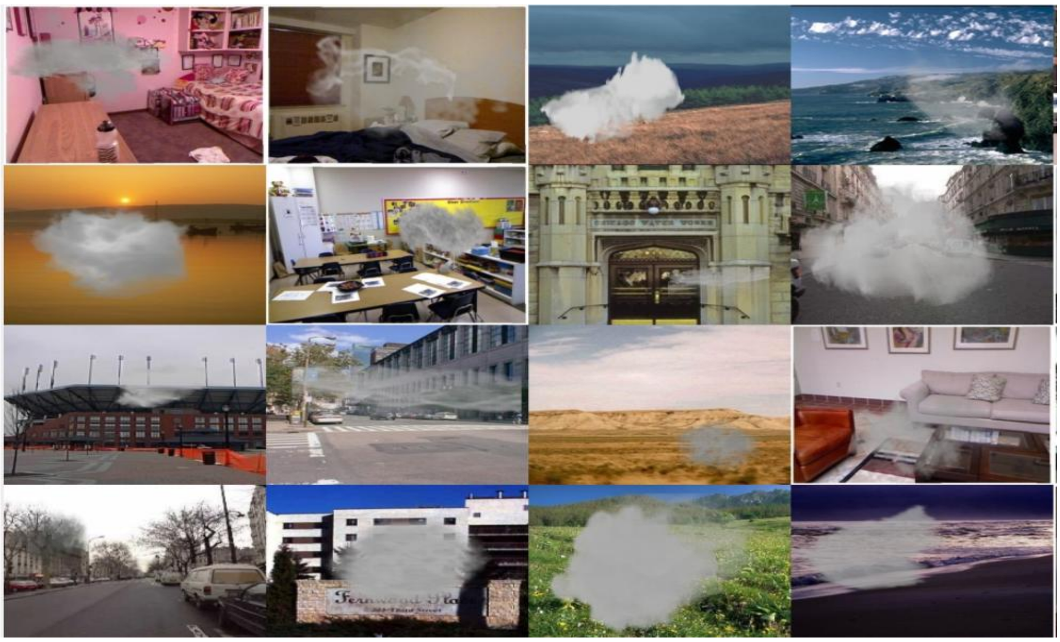

Figure 2: Examples of smoke images

Table 1: Summary of "Smoke 100k" Dataset

Aspect	Details
Total Images	100,000
Image Types	Smoke masks, smoke-free images, annotated bounding boxes
Subsets	Low complexity, Medium complexity, High complexity
Smoke Masks	Synthesized at various angles to simulate real-world conditions
Key Contribution	Addresses challenges in complex smoke detection scenarios

Because of hardware limitations, in this study, we used only 20% of the mentioned dataset, which is equal to 20,000 images, to train and test our model, splitting it evenly between the two classes. In which 10,000 images of scenes containing smoke and 10,000 images without smoke, as shown in Table 2. The dataset was preprocessed by converting the original RGB images into several colour spaces: HSV, YCbCr, LAB, and Grayscale. Every colour space was analyzed for its effect on model performance across training, validation, and testing.

Table 2: Dataset Image Distribution

Category	Images	Details
Smoke Images	10.000	Scenes with visible smoke
No Smoke Images	10.000	Scenes without visible smoke
Total Images	20.000	-

3.2 Implementation Environment

The implementation was carried out on the Kaggle platform, a cloud-based environment designed for machine learning and data science tasks. Kaggle Notebooks, which provide integrated access to datasets, libraries, and GPU resources, were used in all experiments. The hardware specifications included an NVIDIA Tesla P100 GPU (16 GB VRAM), an Intel Xeon Processor (2 cores), and 13 GB of RAM[39]. The environment utilizes Python 3.7.12, alongside libraries such as OpenCV for image preprocessing and colour space transformations, TensorFlow and Keras for building and training the ResNet50 model, NumPy[40] is used for numerical computations, Scikit-learn for dataset splitting and stratified sampling, and Matplotlib and Seaborn for visualizing performance metrics. The ResNet50 model, pre-trained on ImageNet, was modified by adding a Global Average Pooling layer, a Dropout layer (50%), and a Dense layer with a sigmoid activation function for binary classification. The model was compiled using the Adam optimizer with a learning rate of 1e-5 and trained for 50 epochs with early stopping based on validation loss to prevent overfitting.

3.3 Data Preprocessing

To prepare the dataset for smoke detection, images from designated folders containing smoke-free and smoke-laden images were loaded. Only `.png` files were considered for uniformity, and each image was resized to 128x128 pixels for consistency in the input dimensions. The images were then converted to arrays using NumPy and normalized to a range of [0, 1] by dividing the pixel values by 255 to ensure effective neural network training.

Mathematically, the image normalization can be represented as in Equation (1):

$$Xi(new) = \frac{Xi}{255} \quad \dots (1)$$

where Xi represents the original image, and Xi(new) is the normalized image.

The used smoke dataset was divided into 3 (training, validation, and test) groups, and stratified sampling was used to maintain the two-class balance. In detail, the dataset was split into the following portions: 70% training, 15% validation, and 15% testing to ensure a balanced representation of smoke and non-smoke images across all sets.

3.4 Model Architecture

For each image, a different colour space conversion was applied to assess their influence on the smoke detection performance. Images were transformed from the RGB format (the initial state) into the four-colour spaces: HSV, YCbCr, LAB, and Grayscale. This conversion highlights specific visual features that may enhance the model's accuracy in detecting smoke under different conditions. ResNet50, which was already pre-trained on ImageNet [41], was used as the base model for feature extraction. The top layers were removed, and new layers were added, including a Global Average Pooling [42] layer, a Dropout layer with a 50% rate to stop overfitting[43], and finally a Dense layer with a sigmoid activation function for binary classification.

3.5 Model Training

The model was compiled using the Adam optimizer with a learning rate of 1e-5 [44] and binary cross-entropy as the loss function[45]. Early stopping and model checkpoint callbacks were utilized to optimize the training performance and prevent overfitting. The training was performed for 50 epochs with a batch size of 32, monitoring validation loss value to ensure the best model was saved.

3.6 Model Testing

Upon the model's training being completed, its efficacy was evaluated utilizing 15% of the dataset reserved for testing. This assessment sought to evaluate the model's proficiency in accurately categorizing smoke and non-smoke images. The model's predictions on the test set were compared beside the true labels, and a confusion matrix was produced to visualize the classification outcomes. The confusion matrix contains the following components:

- True positives (TP) refer to correctly identified smoke images.
- True-negatives (TN) refer to correctly identified non-smoke images.
- False Positives (FP) (False Positives) refers to non-smoke images incorrectly classified as smoke.
- False-Negatives (FN) (False Negatives) refer to smoke images incorrectly classified as non-smoke.

Using these values, several performance metrics were calculated to assess the model's accuracy and reliability. These systems of measurement include accuracy, precision, recall, and F1-score:

- Accuracy: This determines the overall exactness of the model by dividing the number of correct predictions by the total number of predictions. It is defined as in Equation (2):

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

- Precision: This metric calculates how many images predicted as smoke are actually smoke. It focuses on the positive predictive value, helping to reduce the rate of false positives. Equation (3) for precision is:

$$\text{Precision} = TP/(TP+FP) \quad \ldots \quad (3)$$

- Recall, sometimes called sensitivity or true positive rate, quantifies the model's ability to precisely identify smoke images among all genuine smoke images in the test set. *Equation (4)* for recall is:

$$\text{Recall} = TP/(TP+FN) \quad \ldots \quad (4)$$

- The F1-score is the harmonic means of precision and recall, offering a singular metric that equilibrates false positives and false negatives. Achieving a balance between precision and recall is advantageous. Equation (5) represents the F1-score:

$$\text{F1-Score} = 2*(\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \quad \ldots \quad (5)$$

A comprehensive evaluation of the model's performance was provided by calculating these metrics [46]. Precision highlights the proportion of relevant smoke predictions, recall emphasizes the model's ability to detect smoke instances, and the F1-score assesses both, ensuring a fair estimation when false positives and false negatives are concerned. Additionally, the model's accuracy exhibits its overall performance across both smoke and non-smoke images. By using the 15% test set, these metrics offer a solid assessment of how well the trained model generalizes to unseen data, helping to ensure reliable performance in real-world smoke detection tasks.

4. EXPERIMENTS AND RESULTS

The ResNet50 model was trained for 50 epochs for each colour space, utilizing 70% of the data for training, 15% for validation, and 15% for testing. We give the accuracy and loss during training and validation across all colour spaces, as illustrated in Table 3.

Table 3: Model Performance Across Different Colour Spaces

Colour Space	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
RGB	92.4%	91.3%	0.18	0.22
HSV	93.8%	92.6%	0.14	0.19
YCbCr	91.5%	90.2%	0.20	0.23
LAB	92.1%	91.1%	0.19	0.22
Grayscale	88.3%	86.7%	0.31	0.35

The results indicate that the models using the HSV colour space outperformed the other colour spaces, achieving the highest training accuracy of 93.8% and validation accuracy of 92.6%. The Grayscale model had the lowest performance, indicating that removing colour information negatively affected the detection of smoke, as shown in Fig 3.

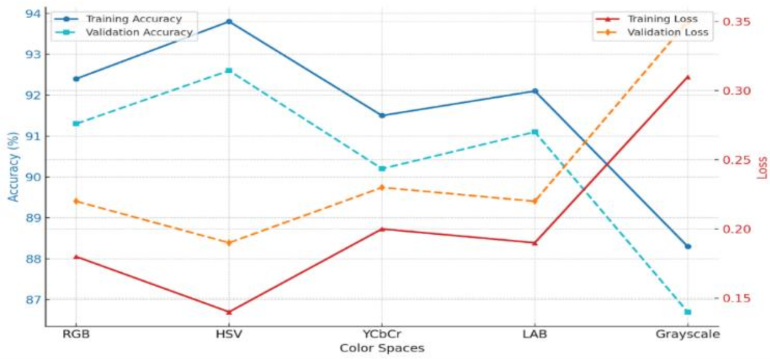

Figure 3: Model Performance Across Different colour Spaces

4.1 Test Results

Upon completing the training process, the models underwent evaluation using the test set. Table 4 presents each colour space's accuracy, precision, recall, and F1-Score. The HSV colour space again showed superior performance in the test phase with a 92.1% accuracy and the highest F1-score of 92.1%. In contrast, the lowest test accuracy of 85.4% was exhibited by the Grayscale model, suggesting that enough visual features necessary for robust smoke detection are not captured by grayscale images Fig 4

Table 4: Test Performance Across Different colour Spaces

Colour Space	Test Accuracy	Precision	Recall	F1-Score
RGB	90.9%	91.2%	90.5%	90.8%
HSV	92.1%	92.3%	91.9%	92.1%
YCbCr	89.8%	90.0%	89.6%	89.8%
LAB	90.6%	91.0%	90.3%	90.7%
Grayscale	85.4%	85.8%	85.0%	85.4%

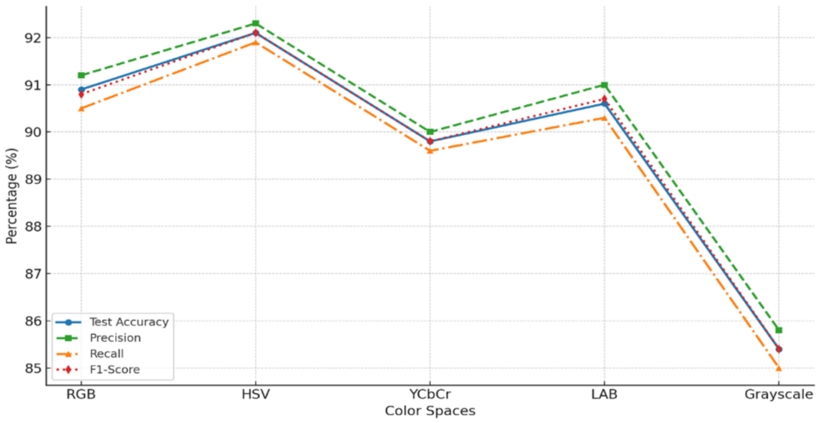

Figure 4: Test Performance Across Different Colour Spaces

4.2 Confusion Matrices

A detailed view of the model's performance is provided by the confusion matrices for each colour space by illustrating the distribution of true positives, true negatives, false positives, and false negatives. Valuable insights into how well the model distinguishes between smoke and non-smoke images across different colour spaces are presented by these matrices. The confusion matrices generated for each colour space are presented in Table 5, highlighting the variations in the prediction accuracy and error distribution. By analysing these matrices, the specific strengths and weaknesses in the model's capability to determine smoke can be identified, depending on the chosen colour space.

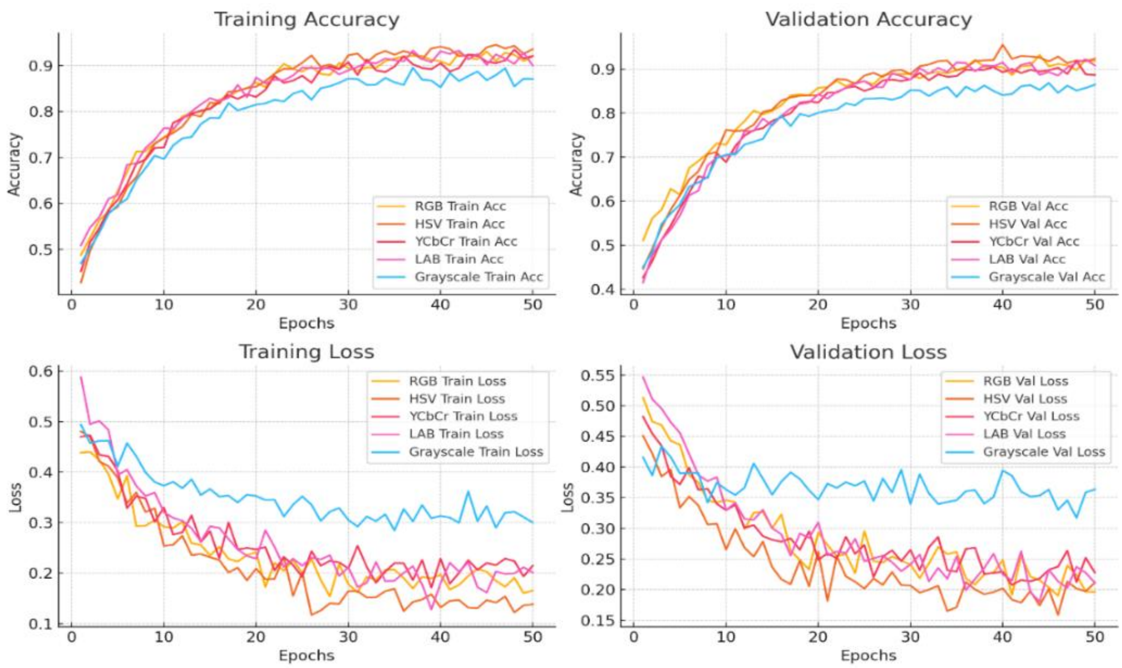

Figure 5: Training and Validation Performance Across Different Colour Spaces

The fewest false positives and false negatives are shown by the HSV colour space confusion matrix, creating it the top performer with regard to balanced predictions. The highest number of false negatives and false positives is exposed by the Grayscale model, representing its difficulty in accurately detecting smoke in images, as shown in Fig 5.

Table 5: Confusion Matrix Results Across Colour Spaces

Colour Space	True-Positives (TP)	True-Negatives (TN)	False-Positives (FP)	False- Negatives (FN)
RGB	4,540	4,560	440	460
HSV	4,620	4,610	390	380
YCbCr	4,480	4,500	500	520
LAB	4,530	4,540	460	470
Grayscale	4,270	4,320	680	730

5. DISCUSSION AND CONCLUSION

The results across different colour spaces are shown by colour information acting as a significant task in smoke detection. The others were consistently outperformed by the HSV colour space, likely due to its capability to separate colour and intensity information, which helps in detecting smoke in inspiring lighting settings. However, considering the worst performance was shown by the grayscale model, as important colour features critical for distinguishing smoke from other elements in the image failed to be leveraged. These results are associated with previous studies that underline the importance of selecting the right colour space for image classification tasks.

Future research should focus on developing a real-time smoke detection system by integrating the current machine-learning models with live video feeds. This would significantly enhance early smoke detection capabilities, particularly in critical applications like forest fire prevention and industrial safety. Additionally, expanding the dataset to include a wider variety of environmental conditions, smoke types, and geographic locations would improve the model's generalization and robustness, especially when incorporating smoke from different fuel sources. Exploring hybrid models that combine convolutional neural networks (CNNs) with other techniques, such as recurrent neural networks (RNNs) or attention mechanisms, may further enhance temporal pattern recognition and overall performance in smoke detection tasks. Another important direction is to deploy the model on edge devices, such as drones or IoT systems, for real-time monitoring in remote or hazardous environments. Optimizing the performance on hardware-constrained devices through techniques like model pruning or quantization could be a key step toward efficient real-world applications. Also, implementing these systems on a smaller device makes real-time monitoring more accessible to everyone.

ACKNOWLEDGMENT

We want to extend our gratefully acknowledge to Middle Technical University, College of Health and Medical Techniques, Baghdad, Iraq, for their invaluable encouragement and support in the publication of this paper.

CONFLICT OF INTEREST

The authors declare that there is *no conflict of interest* regarding the publication of this paper.

REFERENCES

[1] R. N. Vasconcelos et al., "Fire Detection with Deep Learning: A Comprehensive Review," Land, vol. 13, no. 10, p. 1696, Oct. 2024, doi: 10.3390/land13101696.

[2] B. M. Diaconu, "Recent Advances and Emerging Directions in Fire Detection Systems Based on Machine Learning Algorithms," Fire, vol. 6, no. 11, p. 441, Nov. 2023, doi:

10.3390/fire6110441.

[3] O. V. Ekunke et al., "Innovations in Fire Detection and Suppression Systems for Oil Refinery Operations," Path Sci., vol. 10, no. 11, pp. 4001–4015, Nov. 2024, doi: 10.22178/pos.111-7.

[4] W. Y. Hwang et al., "Computational design of a smoke detector with high sensitivity considering three-dimensional flow characteristics," Case Stud. Therm. Eng., vol. 53, p. 103896, Jan. 2024, doi: 10.1016/j.csite.2023.103896.

[5] F. M. Talaat and H. ZainEldin, "An improved fire detection approach based on YOLO-v8 for smart cities," Neural Comput. Appl., vol. 35, no. 28, pp. 20939–20954, Oct. 2023, doi: 10.1007/s00521-023-08809-1.

[6] M. M. Umar, L. C. De Silva, M. S. A. Bakar, and M. I. Petra, "State of the art of smoke and fire detection using image processing," Int. J. Signal Imaging Syst. Eng., vol. 10, no. 1/2, p. 22, 2017, doi: 10.1504/IJSISE.2017.084566.

[7] R. W. Bukowski et al., "Performance of home smoke alarms analysis of the response of several available technologies in residential fire settings," Gaithersburg, MD, 2008. doi: 10.6028/NIST.TN.1455-1r2008.

[8] J. Fang, J. Jie, Y. Hong-Yong, and Z. Yong-Ming, "Early fire smoke movements and detection in high large volume spaces," Build. Environ., vol. 41, no. 11, pp. 1482–1493, Nov. 2006, doi: 10.1016/j.buildenv.2005.05.036.

[9] G. Lin, Y. Zhang, G. Xu, and Q. Zhang, "Smoke Detection on Video Sequences Using 3D Convolutional Neural Networks," Fire Technol., vol. 55, no. 5, pp. 1827–1847, Sep. 2019, doi: 10.1007/s10694-019-00832-w.

[10] K. Lakhwani Associate Professor, P. D. Murarka Professor Arya, and N. Singh Chauhan, "Colour Space Transformation for Visual Enhancement of noisy colour Image," Int. J. ICT Manag., vol. 2, no. October, pp. 2026–6839, 2015.

[11] M. Shafiq and Z. Gu, "Deep Residual Learning for Image Recognition: A Survey," Appl. Sci., vol. 12, no. 18, p. 8972, Sep. 2022, doi: 10.3390/app12188972.

[12] L. Wang, X. Zhang, L. Li, B. Li, and Z. Mei, "Experimental Study on Early Fire Smoke Characteristics in a High-Volume Space: A Fire Detection Perspective," Fire, vol. 7, no. 9, p. 298, Aug. 2024, doi: 10.3390/fire7090298.

[13] S. B and A. P, "Effect of Different Colour Spaces on Deep Image Segmentation," in Proc. 2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), Dec. 2021, vol. 12, no. 3, pp. 1–4, doi: 10.1109/WIECON-ECE54711.2021.9829655.

[14] O. Giwa and A. Benkrid, "A new flame-based colour space for efficient fire detection," IET Image Process., vol. 18, no. 5, pp. 1229–1244, Apr. 2024, doi: 10.1049/ipr2.13022.

[15] C. Emmy Prema, S. S. Vinsley, and S. Suresh, "Multi feature analysis of smoke in YUV colour space for early forest fire detection," Fire Technol., vol. 52, pp. 1319–1342, 2016.

[16] Z. Han, Y. Tian, C. Zheng, and F. Zhao, "Forest Fire Smoke Detection Based on Multiple Colour Spaces Deep Feature Fusion," Forests, vol. 15, no. 4, p. 689, Apr. 2024, doi: 10.3390/f15040689.

[17] H. M. Bui, M. Lech, E. Cheng, K. Neville, and I. S. Burnett, "Using grayscale images for object recognition with convolutional-recursive neural network," in Proc. 2016 IEEE Sixth International Conference on Communications and Electronics (ICCE), Jul. 2016, pp. 321–325, doi: 10.1109/CCE.2016.7562656.

[18] Z. Wang, C. Zheng, J. Yin, Y. Tian, and W. Cui, "A Semantic Segmentation Method for Early Forest Fire Smoke Based on Concentration Weighting," Electronics, vol. 10, no. 21, p. 2675, Oct. 2021, doi: 10.3390/electronics10212675.

[19] S. Q. M. Salih and A. S. A. Khamas, "Exploring Colour s Combinations Impact on the Vision Comfortable and 3D Model Lucidity," Appl. Model. Simul., vol. 4, pp. 31–39, 2020.

[20] T. Liu et al., "Video Smoke Detection Method Based on Change-Cumulative Image and Fusion

Deep Network," Sensors, vol. 19, no. 23, p. 5060, Nov. 2019, doi: 10.3390/s19235060.

[21] M. Chyad et al., "Exploring adversarial deep learning for fusion in multi-colour channel skin detection applications," Inf. Fusion, vol. 114, p. 102632, Feb. 2025, doi: 10.1016/j.inffus.2024.102632.

[22] O. Besbes and A. Benazza-Benyahia, "A novel video-based smoke detection method based on colour invariants," in Proc. 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Mar. 2016, pp. 1911–1915, doi: 10.1109/ICASSP.2016.7472009.

[23] O. Besbes and A. Benazza-Benyahia, "A novel video-based smoke detection method based on colour invariants," in Proc. 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2016, pp. 1911–1915.

[24] W. S. Qureshi, M. Ekpanyapong, M. N. Dailey, S. Rinsurongkawong, A. Malenichev, and O. Krasotkina, "QuickBlaze: Early Fire Detection Using a Combined Video Processing Approach," Fire Technol., vol. 52, no. 5, pp. 1293–1317, Sep. 2016, doi: 10.1007/s10694-015-0489-7.

[25] J. Zhao, Y. Zhou, B. Shi, J. Yang, D. Zhang, and R. Yao, "Multi-stage fusion and multi-source attention network for multi-modal remote sensing image segmentation," ACM Trans. Intell. Syst. Technol., vol. 12, no. 6, pp. 1–20, 2021.

[26] S. Haridasan, A. Rattani, Z. S. Demissie, and A. Dutta, "Multispectral Deep Learning Models for Wildfire Detection.," 2022.

[27] A. S. Pundir and B. Raman, "Deep Belief Network For Smoke Detection," Fire Technol., vol. 53, no. 6, pp. 1943–1960, Nov. 2017, doi: 10.1007/s10694-017-0665-z.

[28] Q. Zhang, G. Lin, Y. Zhang, G. Xu, and J. Wang, "Wildland Forest Fire Smoke Detection Based on Faster R-CNN using Synthetic Smoke Images," Procedia Eng., vol. 211, pp. 441–446, 2018, doi: 10.1016/j.proeng.2017.12.034.

[29] S. Aslan, U. Gudukbay, B. U. Toreyin, and A. Enis Cetin, "Early Wildfire Smoke Detection Based on Motion-based Geometric Image Transformation and Deep Convolutional Generative Adversarial Networks," in Proc. ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2019, pp. 8315–8319, doi: 10.1109/ICASSP.2019.8683629.

[30] K. Gu, Z. Xia, J. Qiao, and W. Lin, "Deep Dual-Channel Neural Network for Image-Based Smoke Detection," IEEE Trans. Multimed., vol. 22, no. 2, pp. 311–323, Feb. 2020, doi: 10.1109/TMM.2019.2929009.

[31] K. Gu, Z. Xia, J. Qiao, and W. Lin, "Deep Dual-Channel Neural Network for Image-Based Smoke Detection," IEEE Trans. Multimed., vol. 22, no. 2, pp. 311–323, Feb. 2020, doi: 10.1109/TMM.2019.2929009.

[32] F. Safarov, S. Muksimova, M. Kamoliddin, and Y. I. Cho, "Fire and Smoke Detection in Complex Environments," Fire, vol. 7, no. 11, 2024, doi: 10.3390/fire7110389.

[33] Z. G. Hadi, A. R. Ajel, and A. Q. Al-Dujaili, "Comparison Between Convolutional Neural Network CNN and SVM in Skin Cancer Images Recognition," J. Tech., vol. 3, no. 4, pp. 15–22, Dec. 2021, doi: 10.51173/jt.v3i4.390.

[34] S. Frizzi, R. Kaabi, M. Bouchouicha, J.-M. Ginoux, E. Moreau, and F. Fnaiech, "Convolutional neural network for video fire and smoke detection," in Proc. IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, 2016, pp. 877–882, doi: 10.1109/IECON.2016.7793196.

[35] D. Singh and B. Singh, "Investigating the impact of data normalization on classification performance," Appl. Soft Comput., vol. 97, p. 105524, Dec. 2020, doi: 10.1016/j.asoc.2019.105524.

[36] T. D. Nguyen, M.-H. Shih, D. Srivastava, S. Tirthapura, and B. Xu, "Stratified random sampling from streaming and stored data," Distrib. Parallel Databases, vol. 39, no. 3, pp. 665–710, Sep. 2021, doi: 10.1007/s10619-020-07315-w.

[37] H.-Y. Cheng, J.-L. Yin, B.-H. Chen, and Z.-M. Yu, "Smoke 100k: A Database for Smoke Detection," in Proc. 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), Oct. 2019, pp. 596–597, doi: 10.1109/GCCE46687.2019.9015309.

[38] Smoke100k, "A Database for Smoke Detection." available: https://bigmms.github.io/cheng_gcce19_smoke100k (accessed Oct. 04, 2024).

[39] "Kaggle." available:https://www.kaggle.com (accessed Oct. 04, 2024).

[40] S. van der Walt, S. C. Colbert, and G. Varoquaux, "The NumPy Array: A Structure for Efficient Numerical Computation," Comput. Sci. Eng., vol. 13, no. 2, pp. 22–30, Mar. 2011, doi: 10.1109/MCSE.2011.37.

[41] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in Proc. 2009 IEEE conference on computer vision and pattern recognition, 2009, pp. 248–255.

[42] M. Lin, "Network in network," arXiv Prepr. arXiv1312.4400, 2013, doi: 10.48550/arXiv.1312.4400.

[43] H. Li, J. Li, X. Guan, B. Liang, Y. Lai, and X. Luo, "Research on Overfitting of Deep Learning," in Proc. 2019 15th International Conference on Computational Intelligence and Security (CIS), 2019, pp. 78–81, doi: 10.1109/CIS.2019.00025.

[44] H. Iiduka, "Appropriate Learning Rates of Adaptive Learning Rate Optimization Algorithms for Training Deep Neural Networks," IEEE Trans. Cybern., vol. 52, no. 12, pp. 13250–13261, Dec. 2022, doi: 10.1109/TCYB.2021.3107415.

[45] S. Mannor, D. Peleg, and R. Rubinstein, "The cross entropy method for classification," in Proc. 22nd International Conference on Machine Learning, 2005, pp. 561–568, doi: 10.1145/1102351.1102422.

[46] R. Yacouby and D. Axman, "Probabilistic Extension of Precision, Recall, and F1 Score for More Thorough Evaluation of Classification Models," in Proc. First Workshop on Evaluation and Comparison of NLP Systems, 2020, pp. 79–91, doi: 10.18653/v1/2020.eval4nlp-1.9.