International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

Detection of Micro Plastics in Human Lung Tissues: Using Matlab-Based CNN

Chandanikanwar Udaysingh Sodha[1], Prof. Jyoti M. Waykule[2]
[1]PG Scholar, Dept. of Electronics & Comunications, Sanjay Ghodawat University, Kolhapur, Maharastra, India.
[2]Asst. Prof, Dept. of Electronics & Comunications, Sanjay Ghodawat University, Kolhapur, Maharastra, India.
Emails: *Er.chandanisodha@gmail.com[1], jyoti.waykule@sanjayghodawatuniversity.ac.in[2]*

Abstract
The smaller particles found in the surrounding, are smaller in size 5mm or less, commonly known as Microplastics. These small residues can enter human body through respiration, ingestion and also sometimes through exposure and wounds. These particle infusions in human beings is raising serious concern and having harmful effects on human body. Now-a-days these particles are commonly found in human organs that leads to future health issues. This study focus on detection of Micro-plastics in human lungs using approach based on Matlab. In this paper, the convolutional neural network process is combined with image-processing methods to detect the presence of microplastics in human tissue. The detection involves several steps including: enhancement of image, region of interest extraction and performance analysis of methodology. The motive of this study is to reduce the manual work and using technology in prominent ways.
Keywords: *CNN, Human Lung, Tissue, Image Processing, Means Segmentation, MATLAB, Microplastics.*

1. Introduction
Microplastics are the small finer particles of plastic, less then 5mm in size, are a type of pollutant commonly found in atmosphere. The main source of origin of these particles are from synthetic and industrial waste, layer-degradation of plastic based artifacts around us [1]. Because of their small size, they can easily enter human body and are commonly detected in different human organs such as lungs, bloodstream, liver, heart and kidney. Due to them, we are facing a serious health thread [2,3]. These particles induce in human body using various ways like while inhaling air, and through food and water which leads to damage internal organs and tissues and long term health problems [4]. Mostly the intake occurs through respiration, so the organ majorly affected by microplastics is human lungs, especially for those who are more exposed to airborne particles in the surrounding. This exposure raise the harmful effect significantly [3][6]. Currently the problem occurs in detection of microplastics in human tissue is because of small size and similarities with the other tissue of lungs [7][8]. There are several conventional methods for detection such as Microscopy, FTIR and Raman spectroscopy are more effective but have high initial and processing cost and more human interface is requiring during the process and take more time in processing [5][9]. Due to these issues, the advancement in detection is needed with more automation and digital approaches. This work is aimed at detecting the presence of microplastics in tissue of human lung with the help of image processing technologies and CNN. Although, traditional techniques are more effective but slow and are more based on human efforts. Apart from that, current approaches are more fast and show results accurately. these automation helps in reduction of human errors as well as involvement, quick detection with multiple screening. highlight the regions, where microplastic is detected [1]

2. Literature Review
Table 1 shows Overview of Literatures in The Field of Microplastics Detection

Table 1 Overview of Literatures in The Field of Microplastics Detection

Title	Authors	Publisher/Year	Overview	Technique Used	Conclusion	Advantages	Limitations
Microplastics in Air. Are WeBreathing It In?	J. Gasperi et al.	Curr. Opin. Environ. Sci. Health, 2018	Reviews airborne microplastics, their sources, and health risks	Atmospheric sampling; chemical analysis	MPs found in air and indoor spaces, posing health risks.	Highlights MP ubiquity and risks.	Lacks long-term exposure data
Human Consumptionof Microplastics	K. D. Cox et al.	Environ. Sci. Technol., 2019	Evaluates human ingestion of MPs from food and air	Literature review; spectroscopy and molecular analysis	Substantial annual MP intake from various sources.	First large-scale MP consumption study.	Limited food group coverage; outdated methods.
Presence of airborne microplastics in human lung tissue	L. F. Amato Lourenço et al.	J. Hazard. Mater., 2021	Detects MPs in human lung tissue, suggesting inhalation as exposure route.	Microscopy; chemical analysis	Confirms MPs in lungs, urging further research.	Highlights inhalation as key exposure route.	Small sample size; potential contamination.
Detection of Microplastis in Human Tissues and Organs: A Scoping Review	N. S. Roslan et al.	J. Glob. Health, 2024	Reviews MP detection in human tissues and organs.	Systematic review; spectroscopy microscopy; chemical analysis	Finds MPs in organs, calls for further study.	Comprehensive overview of MP detection.	No standardized detection; limited long-term data.
Detection of Microplastics in Human Lung Tissue Using	L. C. Jenner et al.	Sci. Total Environ., 2022	Uses FTIR spectroscopy to identify MPs in lung tissue.	FIR spectroscopy	Shows polypropylene and PET fibers in lung regions.	Provides evidence of pulmonary MP accumulation.	Limited samples; no causation.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

FTIR Spectroscopy							
The environment al fate of microplastic particles originating from artificial sports turfs	L. H. Mortensen et al.	Sci. Total Environ., 2021	Examines MPs from artificial turf, their dispersal, and ecological effects.	Literature review; field sampling; simulations	Identifies turf as a significant MP source; suggests mitigation	Highlights turf as an MP source.	Uncertain long-term effects.
Detection of Exposure to Microplastics in Humans: A Systematic Review	Various authors	Open Access Maced. J. Med. Sci., 2021	Reviews human MP exposure, summarizing detection methods.	Literature review; data extraction	Confirms MP presence in humans; further research needed.	Broad overview of human MP exposure.	Limited by study quality.
Microplastic sin Environment : Global Concern, Challenges, and Controlling Measures	G. Lamichhane et al.	Environ. Sci. Pollut. Res., 2022	Reviews global MP pollution and mitigation measures.	Literature review; data synthesis	Calls for global cooperation on MP control.	Comprehensi ve review; solution-focused.	Lacks new experimental data
An emerging role of microplastics in the etiology of lung ground glass	Q. Chen et al.	Environ. Sci. Europe, 2022	Links airborne MPs to lung ground glass nodules.	Microscopy; FTIR; chemical characterization	Suggests association between MPs and lung abnormalitie 5.	Raises awareness of MP health risks.	Small sample size, no long-term data

nodules							
Enhanced Multi Resolution CNN Models for Lung Nodule Identification and Segmentation in CT Images	P. Rajyalakshm i et al.	Int. J. Comput. Sci. Eng., 2023	Proposes multi-resolution CNN for lung nodule detection.	Multi-resolution CNN	Improves small-nodule detection.	Better nodule detection and feature fusion.	Higher computational demands.
Multi Scale Convoluti on al Neural Networks for Lung Nodule Classification	W. Shen et al.	Proc. Int. Conf. Information Processing in Medical Imaging, 2017	Uses multi-scale CNN for nodule malignancy prediction.	Multi-scale CNN; hierarchical classification	Outperforms single-scale methods with high accuracy.	Captures fine and contextual features.	Sensitive to scale selection.
ImageNet Classificatio n with Deep Convoluti on al Neural Networks	A. Krizhevsky et al.	Adv. Neural Inf. Process. Syst., 2012	Demonstrate s deep CNNs (AlexNet) on ImageNet, introducing key innovations.	Deep CNN (AlexNet); ReLU; pooling; augmentation	Pioneering deep CNNs for image tasks.	Robust generalizatio n and performance.	Requires large data/training.

3. Methodology

The methodology used for the detection of microplastic particle in human tissue includes two steps: initially detection using CNN approach and Localisation using K-mean segmentation. The approach with the help of the flow chart mentioned below that explains steps involved in the processing with input data. [2]

3.1. Microplastic Detection Using CNN

In the initial step, supervised learning is done with the help of CNN model. The step starts with preparation of dataset of training images. The quality of the image is automatically improved using the inbuilt enhancement processing in Matlab. After this to reduce the load on computational approach, these images were resized to ensure same input dimensions. A simple architecture of CNN is used with basic convolutional and all layers are fully connected. This network trained to follow basic parameters including learning rate, accurate classification optimisation, number of epochs and batch size. After that, the model is saved for further use. Under testing, a fresh query image is enhanced and resized. Later, the process runs to detect the presence of microplastic in image, if detected, the next step of localization initiated. preparation, image enhancement, resizing, training the CNN, and testing with a query image. If microplastic is detected, the system proceeds to localization.) [3]

3.2.Microplastic Localization Using K-Means Segmentation

After the initial detection, if the presence of foreign particle confirms, the system proceeds to detect the region where the particle is detected in the image. The non-enhanced image is used in this step to prevent removal of spatial details. Then both results of enhanced and non-enhanced image compared to find accurate segmentation. Later, a special learning method "K-means clustering" is applied to image. This step involved separation of image pixels on the basis of intensity and color, and highlight the regions, where microplastic is detected. After segmentation, region of interest (ROI) were identified, the highlighted region show the potential area where particles are likely to found. This step helps in better understanding the region and for further analysis Figure 1. Shows Overall framework for microplastic detection using CNN. (The process includes dataset preparation, image enhancement, resizing, training the CNN, and testing with a query image. If microplastic is detected, the system proceeds to localization.)

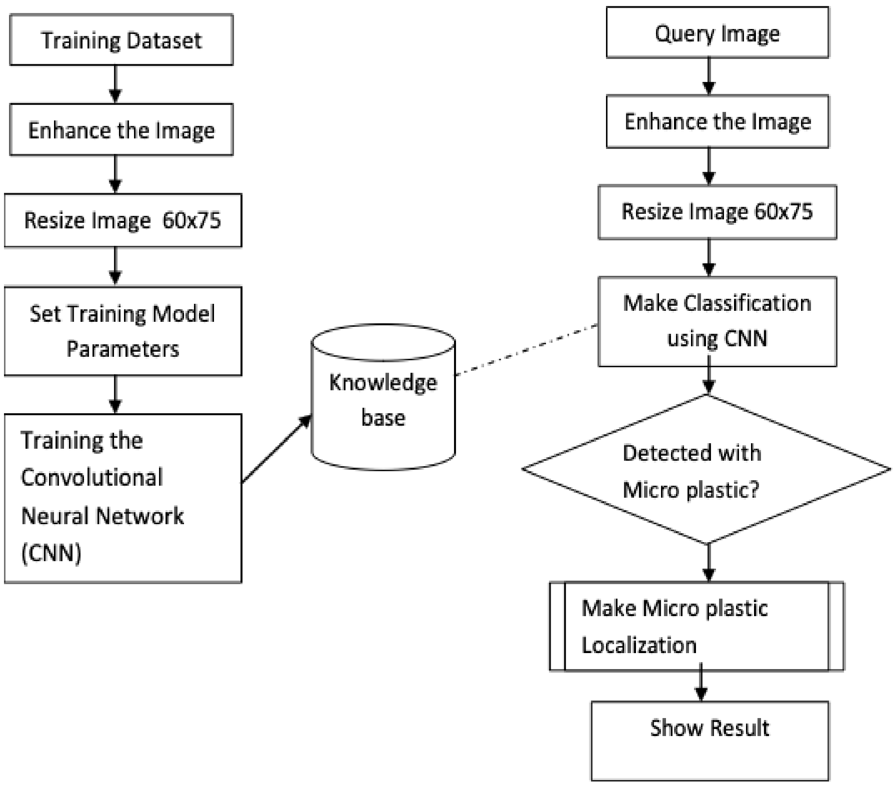


Figure 1 Overall Framework for Microplastic Detection Using CNN. (The Process Includes Dataset Preparation, Image Enhancement, Resizing, Training The CNN, and Testing with A Query Image. If Microplastic Is Detected, The System Proceeds to Localization)

IRJAEH

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

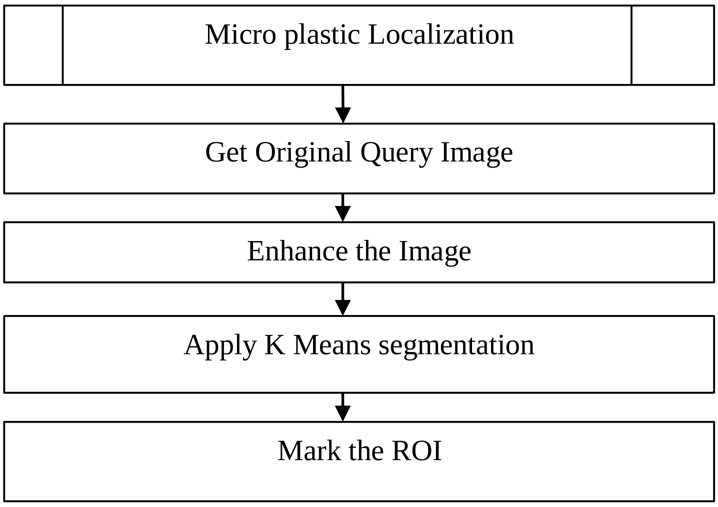


Figure 2 Microplastic Localization Using K-Means Segmentation. The Process Includes Enhancement of the Original Image, Pixel Clustering with K-Means Algorithm, And Marking the Regions of Interest (ROI) Where Microplastics Are Identified

4. Result

This part focus on the evaluation of results for the proposed model of detection of microplastics using microscopy images of lung tissue. The effectiveness of the used model is verified with the help of analyzing confusion matrix, calculating metrics of performance and observing training progress.

4.1.Confusion Matrix and Performance Analysis

The above figure 3 is the performance analysis result stated that the model detected 7 true cases of microplastics present as shown in (TP) and labelled 2 clean cases in (FN), whereas it to detect 6 actual samples negative (TN) and labelled 3 false samples as positive in (FP). The matrix achieved the accuracy of 72.22% and detected almost 3/4 samples correctly. The program has sensitivity of 77.78% means, the model detects real microplastics more often and specificity of the model is 66.67% that states the ability to recognize clean samples. Out of 10 samples, 7 detections were actual microplastics, thus the preciseness of the model is 70%, while the 1/3 of the positives are actually negative and hence the false positive value of the model is around 33.33%. Overall this model performs well in terms of detection of microplastics but there are still some improvement needed towards false alarms and misses. [5]

```
-----------------------------
      | Positive | Negative |
-----------------------------
True |          7|         6|
-----------------------------
False|          3|         2|
-----------------------------
Accuracy = 72.22 %
Sensitivity = 77.78 %
Specificity = 66.67 %
True Predicative Value = 70.00 %
False Positive Value= 33.33 %
```

Figure 3 Performance Analysis (This Correctly Predicts 7 True Positives and 2 True Negatives, with 6 False Negatives and 3 False Positives, Achieving an Overall Accuracy of 72.2%) Performance Analysis Shows, Where The Model

The figure 4 illustrate the confusion matrix I normalised way for CNN classifier, in which, column represents “0” for no micro particle and “1” for micro particles. The row in the figure states models predictions. In the cell (0,0), the model identify 6 out of 8 negative samples with accuracy of 75%, while in (0,1), 2 negative samples were classified as positive with precision of 25%. Also in cell (1,0),

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

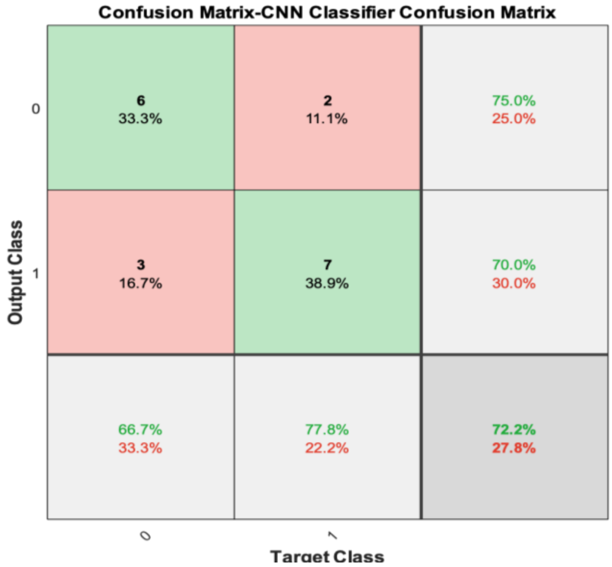


Figure 4 Confusion Matrix (Figure Shows the Normalized Confusion Matrix for Our CNN Classifier, Where The Columns Represent the Actual (Target) Classes "0" For No Microplastics and "1" For Microplastics and The Rows Represent the Model's Predictions)

the model detected 3 positive samples as negative out of 10 and in (1,1), the model identify 7 out of 10 samples positive with 70%. In conclusion, the specificity and false-positive for "no micro particle" is 75% and 25% respectively whereas for "micro particles" the model sensitivity is 77.8% and rate of detecting false-negative is 22.2%. The figure shows the overall accuracy of 72.2% which means 7 out of 10 samples were detected correctly. Figure 4 shows Confusion Matrix (Figure Shows the Normalized Confusion Matrix for Our CNN Classifier, Where The Columns Represent the Actual (Target) Classes "0" For No Microplastics and "1" For Microplastics and The Rows Represent the Model's Predictions)

4.2.Training Progress Analysis

The training performance of the model was checked with help of accuracy and loss trends as shown in table below. At the beginning (Epoch 1), the accuracy of mini-batch is 57.69% whereas the loss of mini-batch is 5.3736, which indicate the initial stage of learning. At (Epoch 50), the accuracy reached upto 100% and the loss reduced to 0.0004. Further at Epoch 69, the accuracy remained at 100% whereas the loss decreases significantly to 0.000072. The base learning rate remain constant during the process at 0.0001 to ensure stable convergence. This results in demonstration of ability of model to learn effectively and generalisation of data without outfitting. Table 2 Training Progress Analysis Shows the Mini-Batch Accuracy Increasing from 57.69% To 100%, And Loss Reduces from 5.3736 To 7.2 × 10^{-5} Over 69 Epochs, Indicating Stable Convergence and Effective Learning [6]

Table 2 Training Progress Analysis Shows the Mini-Batch Accuracy Increasing from 57.69% To 100%, And Loss Reduces from 5.3736 To 7.2 × 10^{-5} Over 69 Epochs, Indicating Stable Convergence and Effective Learning

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-Batch (Accuracy)	Mini-batch (Loss)	Base Learning Rate
1	1	00:00:01	57.69%	5.3736	1.0000e-04
50	50	00:00:54	100.00%	0.0004	1.0000e-04
69	69	00:01:14	100.00%	7.2168e-05	1.0000e-04

4.3.Receiver Operating Characteristic (ROC) Curve Analysis

The ROC curve is used to illustrate the classification done by CNN classifier, how precisely distinguishing microplastic-postive and negative samples. In this graph, false positive rate was plot against the true positive rate at different threshol levels. The gray diagonal line, which acts as base line, shows random performance with Area Under the Curve(AUC) of 0.5. the ROC curve for the CNN model rises rapidly

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

towards the top-left, determine the high true positive rate and then low false positive rate. This curve reflects that model have strong ability of classification. As shown in figure, the AUC value above 0.9 shows deflection in curve confirms that model have ability to differentiate between difference classes over the range of threshold levels. Figure 5 shows ROC curve of the CNN Model for Classifying Microplastic and Non-Microplastic Samples. The Curve Shows High Sensitivity with A Low False Positive Rate, Indicating Strong Classification Performance (AUC > 0.9) [7]

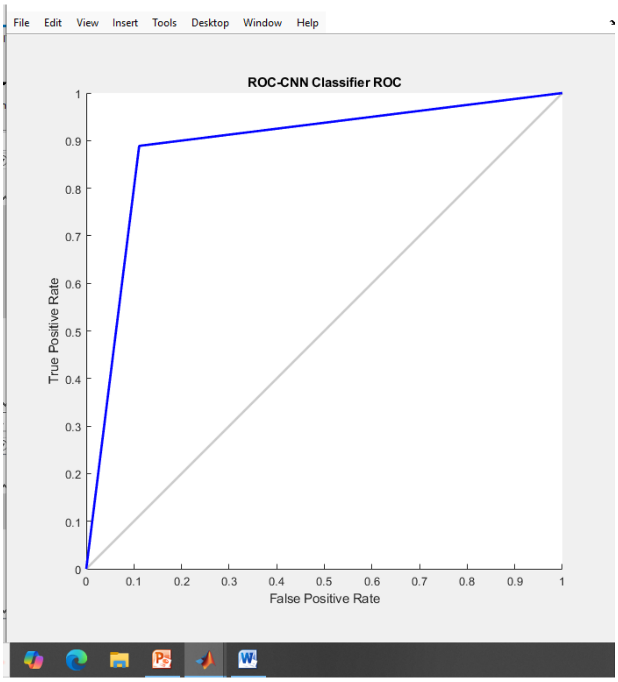


Figure 5 ROC curve of the CNN Model for Classifying Microplastic and Non-Microplastic Samples. The Curve Shows High Sensitivity with A Low False Positive Rate, Indicating Strong Classification Performance (AUC > 0.9)

4.4.Detection Result on a Single Image

To check the realise capability of CNN system, the test images were processed and analysed individually. The below section shows two different images in which microplastic detected and one sample and there other one have no presence of microplastics. To highlight the results and visual representation, the detection includes size rearrangement, image enhancement, K-means clustering and segmentation. [8]

4.5.Microplastic Detected Sample

To show the full process, a microscope image was used which shows positive for the presence of microplastic. Initially the image was resized as per the input requirement parameters for the CNN model. Later, to detect microplastic region and top improve the contrast, image enhancement was performed. After that, K-means clustering was applied to the region of microplastic detected. This process combines the similar looking part together to improve the possibility of detection of microplastic regions. At last, segmentation was done to separate and highlight the presence of microplastic in the image. Results of the above process were illustrated in the figure 6 and 7.

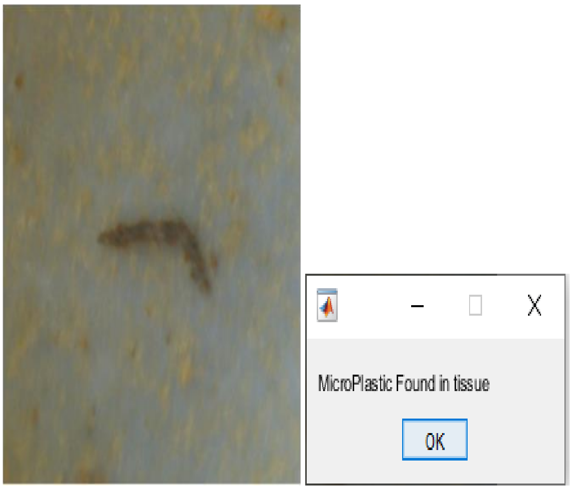
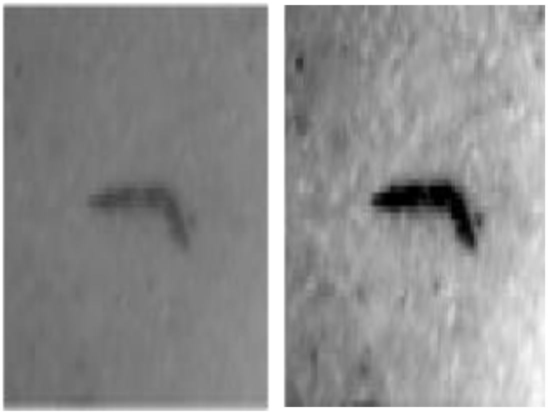


Figure 6 CNN Prediction Result Showing Microplastic Detected in The Tissue Sample



International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3294-3304
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0484

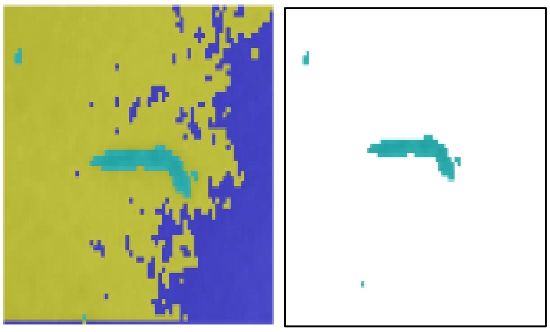


Figure7 Step-by-Step Processing of a Microplastic-Positive Sample: (a) Resized Image, (b) Enhanced Image, (c) K-means Output, (d) Segmented Image

4.6.Microplastic Not Detected (Healthy Tissue)

This part indicates an example of image of a healthy lung tissue, where no microplastics were found. This image undergoes the same process as of a positive sample image. After the process, the results show that lung tissue does not contain any microplastics. The steps were followed for all the image weather they contain microplastics or not. For the image used this time, K-means clustering and segmentation does not highlight and regions for potentials microplastics, as the tissue used was healthy. Below figure 8 shows the result of the following. Figure 8 shows CNN Model Result Showing a Healthy Lung Tissue Sample with No Microplastic Detected [9]

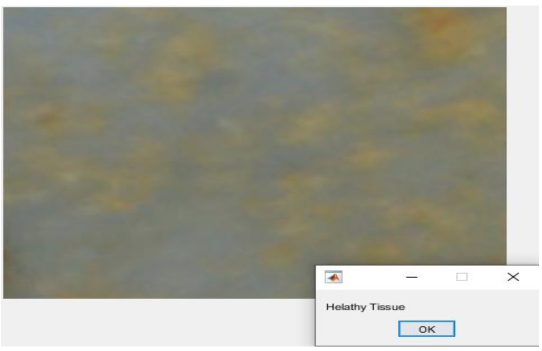


Figure 8 CNN Model Result Showing a Healthy Lung Tissue Sample with No Microplastic Detected

4.7.Model Performance Comparison

In this section, the comparison was done between SVM and CNN models on the basis of metrics, accuracy, sensitivity, specificity, etc.

4.8.Confusion Matrix Analysis

The classification of microplastics positive and negative images was done by confusion matrix for both SVM and CNN. The matrix represents true positives (TP), true negatives (TN), false positive(FP), false negative(FN). After the process, the CNN shows more true positives and true negatives in terms of performance as compared to SVM. In conclusion, CNN performs better in terms of detection of microplastics in image and avoid false alarms.

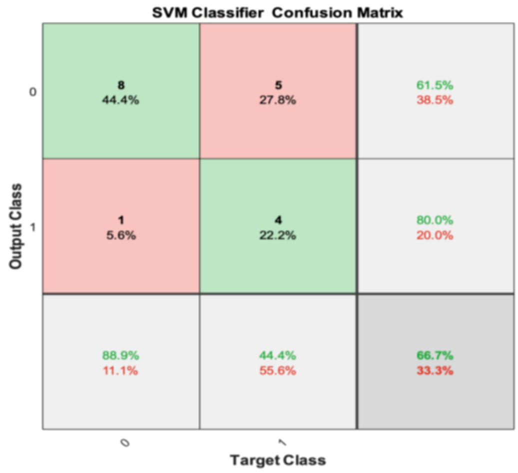


Figure 9 Confusion Matrix for SVM and CNN Models (Ref. Figure 4)

4.9. Performance Metrics Comparison

The table below compares the key metrics for SVM model is for CNN reference figure 3.

	Positive	Negative
True	4	8
False	1	5

Accuracy = 66.67 %
Sensitivity = 44.44 %
Specificity = 88.89 %
True Predicative Value = 80.00 %
False Positive Value= 11.11 %

Figure 10 SVM Performance Analysis

In conclusion, all the results shows that CNN outperform as compared to SVM in terms of accuracy(72.22% vs 66.67%) and sensitivity(77.78% vs 44.44%) as shown in above figure 10, which indicates that CNN is more capable in detection of microplastics. Whereas SVM shows higher specificity(88.89% vs 66.67%) then CNN, that means SVM identify negative sample with more precision but it low sensitivity shows that it may missed positive samples. Overall, CNN show balanced performance, making it more reliable method then SVM. (Figure 10 & 11)

4.10. Bar Chart Comparison

The below bar diagram compares the performance metrics of CNN and SVM model. This figure helps us to graphically understand the difference in accuracy, sensitivity, etc for both the models.

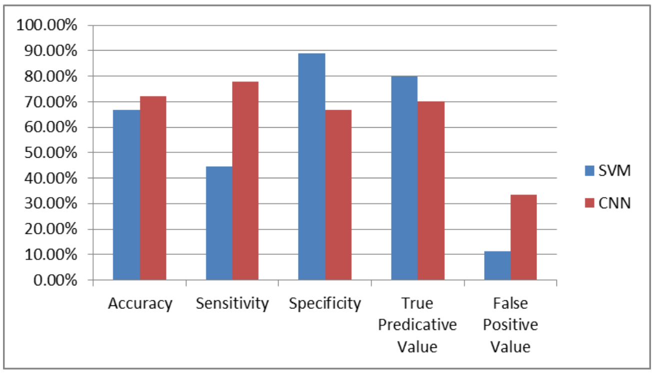


Figure 11 Bar Chart Comparing Performance Metrics for SVM and CNN Models

5. Discussion

Overall outcome of this study demonstrates the use of machine learning models like SVM and CNN in the fields of detection of micro particles in human lung tissues. Results concluded that CNN model provides more reliable outcomes in terms of sensitivity and accuracy, making it best choice for detection. The techniques used in preprocessing like resizing, image enhancement, K-means clustering plays an important role in image quality improvement, helps model to focus only on area of interest. These results show the need of development of such applications or systems in medical field to detect the microplastics in human body, also have potential use in the field of environment monitoring.

Conclusion

The conclusion of the study suggested that CNN model perform better then SVM in detection of microplastics, particularly in terms of sensitivity and accuracy. Although, CNN shows more false positive and hence more refinement is required in the model for more balanced and enhanced results. Additionally, SVM shows better specificity whereas lower accuracy and sensitivity, overall outcomes make SVM less reliable for the detection model. Several study also stated that sensitivity plays the key role in achieving accurate detection for such models.

Future Work

This field has more potential in terms of future research like exploring more advance CNN architectures with the help of ResNet and DenseNet, as these architectures are capable of detecting more complex features but on the other hand require more datasets to optimize performance. By using combination of CNN and SVM can helps use to achieve both good sensitivity as well as specificity. Also, adding more real-world samples to testing models and practical improvements in datasets would be help in creating more robust and reliable models for real life applications.

Reference

[1]. J. Gasperi, S. L. Wright, R. Dris, A. Collard, P. Mandin, A. Guerrouache, E. Langlois, and N. Tassin, “Microplastics in Air: Are We Breathing It In?,” Curr. Opin. Environ. Sci. Health, vol. 1, pp. 1–7, 2018.

[2]. K. D. Cox, G. A. Covernton, H. L. Davies, J. F. Dower, F. Juanes, and S. E. Dudas, “Human Consumption of Microplastics,” Environ. Sci. Technol., vol. 53, no. 12, pp. 7068–7074, 2019.

[3]. L. F. Amato Lourenço, R. Carvalho Oliveira, G. Ribeiro Júnior, L. dos Santos Galvão, R. A. Ando, and T. Mauad, “Presence of Airborne Microplastics in Human Lung Tissue,” J. Hazard. Mater., vol. 403, pp. 123456, Jan. 2021.

[4]. N. S. Roslan, Y. Y. Lee, Y. S. Ibrahim, S. T. Anuar, K. M. K. Yusof, L. A. Lai, and T.

Brentnall, "Detection of Microplastics in Human Tissues and Organs: A Scoping Review," J. Glob. Health, vol. 14, p. 04076, 2024.

[5]. L. C. Jenner, J. M. Rotchell, R. T. Bennett, M. Cowen, V. Tentzeris, and L. R. Sadofsky,"Detection of Microplastics in Human Lung Tissue Using FTIR Spectroscopy," Sci. Total Environ., vol. 806, p. 150492, 2022.

[6]. L. H. Mortensen, K. Syberg, S. Foss Hansen, and J. Vollertsen, "The Environmental Fate of Microplastic Particles Originating from Artificial Sports Turfs," Sci. Total Environ., vol. 781, p. 146706, 2021.

[7]. Sarinah Basri K, Anwar, Daud Basri K, "Detection of Exposure to Microplastics in Humans: A Systematic Review," Open Access Maced. J. Med. Sci., vol. 9, no. 1, pp. 1–10, 2021.

[8]. G. Lamichhane, A. Acharya, R. Malla, S. Adhikari, S. Bhattarai, T. Ghimire, and R. Dhakal, "Microplastics in Environment: Global Concern, Challenges, and Controlling Measures," Environ. Sci. Pollut. Res., vol. 29, pp. 42345–42360, 2022.

[9]. Q. Chen, J. Gao, H. Yu, H. Su, Y. Yang, Y. Cao, Q. Zhang, Y. Ren, H. Hollert, H. Shi, C. Chen, and H. Liu, "An Emerging Role of Microplastics in the Etiology of Lung Ground Glass Nodules," Environ. Sci. Europe, vol. 34, no. 1, p. 24, 2022.