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Dust Prediction

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***Abstract*— In the current context of urbanisation, there is a growing significance in comprehending particulate matter, particularly dust. In spite of its outwardly innocuous characteristics, dust encompasses a multitude of varieties, each possessing unique sources, compositions, and ramifications for both human well-being and the natural surroundings. The presence of diverse dust particles calls for attention in multiple sectors, such as environmental monitoring, healthcare, and archaeology. In response to this requirement, our study introduces an innovative mobile apparatus that incorporates a microscope, is operated by a Raspberry Pi (Rpi) module, and housed within a specially designed enclosure produced through 3D printing technology. At the core of its operational capabilities lies the Region-based Convolutional Neural Network (RCNN), which empowers the device to accurately identify and categorize various dust particles, achieving an 80% precision rate. This novel instrument provides insights that were previously attainable solely through advanced laboratory equipment, representing a noteworthy progression in portable solutions for environmental monitoring.**

Keywords—Dust Prediction, RCNN, Rpi, Urbanisation, Machine Learning, Health Care, Environment

I. INTRODUCTION

In our increasingly complex and urbanised environment, the significance of understanding the particulate matter that surrounds us has grown exponentially. Dust, an omnipresent component of this particulate matter, isn't as innocuous as it might seem at first glance. Beyond its conventional definition as minute solid particles suspended in the atmosphere, dust encompasses a broad spectrum of types, each with unique origins, compositions, and impacts on human health and the environment. Recognising the diversity of dust particles is pivotal for sectors ranging from environmental monitoring to healthcare, archaeology, and beyond.

A. Explanation of the importance of identifying dust types for allergy medication

Allergic reactions, which rank among the foremost health concerns globally, are driven by the immune system's response to seemingly harmless substances. Dust, in this context, is a significant culprit, yet it's a broad term encompassing a variety of particles, not all of which trigger allergies. Delving deeper, household dust can be a cocktail of pollen, mold spores, pet dander, dust mites, and insect waste, each potentially allergenic to different individuals. The ability to identify specific dust components is paramount. Recognizing the exact type of dust present enables medical professionals to prescribe more tailored and effective treatments. This specificity also provides a foundation for healthcare providers to devise personalized allergy management plans, encompassing both medication and environmental adaptations. Beyond immediate treatment, understanding the allergens allows individuals to take proactive preventive measures. For instance, a person allergic to pollen but indifferent to pet dander might reevaluate their choice of houseplants while continuing to enjoy the company of pets. Furthermore, as the medical community refines its grasp on the myriad dust types and their allergenic properties, it creates an avenue for pharmaceutical innovations, leading to medications that are not only more effective but also exhibit fewer side effects. Public health entities, armed with this knowledge, can better educate and guide the public on mitigating allergen exposure. Additionally, consistent identification of dust types in diverse environments holds the potential for more extensive allergen monitoring, which is a cornerstone for evidence-based public health advisories. In essence, accurately determining the components of dust isn't a mere academic exercise; it's a critical endeavor with far-reaching implications for allergy sufferers and the medical community at large.

B. Overview of current methods for detecting dust types

Detecting and analyzing the types of dust present in our environment has garnered significant importance across disciplines from environmental science to health care. Traditional methods such as optical microscopy have long been employed to visually inspect, count, and sometimes infer the potential composition or origin of particles based on their size, shape, and color. However, with advancements in technology, more sophisticated techniques like Scanning Electron Microscopy (SEM) have emerged, offering high-resolution images and, when paired with energy-dispersive X-ray spectroscopy (EDS), detailed elemental composition data of dust particles. Gravimetric analysis, another prevalent technique, gauges the amount of dust captured on a filter within a specified timeframe, providing insights into concentrations when paired with other detection methods. For a more nuanced understanding, especially of organic compounds or biological matter in dust, Fourier Transform Infrared Spectroscopy (FTIR) is employed, leveraging the characteristic absorption of infrared light by materials. In environmental or geological contexts, X-ray Diffraction (XRD) proves invaluable, identifying the mineralogical components of dust samples. Aerodynamic Particle Sizers and Laser Doppler Velocimetry offer real-time particle size distribution measurements and classifications based on particle velocity, respectively. For dust with potential biological significance, bioassays and molecular methods, such as Polymerase Chain Reaction (PCR), are indispensable in pinpointing specific allergens or microbial entities. An exciting frontier in dust detection is the adoption of machine learning and image recognition. Techniques like the Region-based Convolutional Neural Network (RCNN) leverage artificial intelligence to analyze and classify dust images with impressive speed and accuracy. In essence, the landscape of dust detection methodologies is expansive, seamlessly blending age-old techniques with the cutting-edge, promising ever-enhanced insights into the particulate world that surrounds us.

C. Introduction of the proposed portable device for dust type detection

Addressing these challenges, we introduce a novel portable device designed specifically for the detection and classification of different dust types. This compact tool, seamlessly integrating a powerful microscope with a cutting-edge computational unit, promises the marriage of precision with portability. Built around a Raspberry Pi (Rpi) framework, it offers computational prowess in a pocket-sized form. Encased in a custom 3D enclosure, the device not only ensures durability but also user-friendliness, making dust analysis accessible even for the non-expert. The heart of its functionality lies in its advanced classification algorithm based on the Region-based Convolutional Neural Network (RCNN). This ensures that the device doesn't just detect dust particles but classifies them with an accuracy that rivals more cumbersome, traditional setups.

In summary, this proposed device stands at the forefront of environmental monitoring tools. It democratizes the process of dust detection and analysis, allowing for immediate insights whether in urban centers, remote field locations, or personal living spaces. As we venture further into the 21st century, tools like these will be pivotal in shaping our understanding of, and response to, the microscopic world that has macroscopic implications for our planet and its inhabitants.

LITERATURE REVIEW

Allergies, stemming from various sources including insects and atmospheric agents, pose significant health challenges worldwide. In a comprehensive investigation on allergic reactions not caused by insect stings or bites, Guillet et al. expound on allergies arising from the inhalation and ingestion of insects or insect compounds [1]. With the European commercial licensing of mealworms as consumable food in 2021, the study suggests that allergic reactions and cross-reactivities to insects, especially in individuals already allergic to seafood or house dust mites, will see a surge in occurrence [1].

Focusing on children's allergies, Trusova et al. sought to determine the diagnostic significance of various allergological diagnostics for allergies to house dust mites (HDM) in children diagnosed with allergic rhinitis or in conjunction with asthma [2]. Their findings underscored the importance of skin prick tests (SPT) as a primary investigative method, especially given its higher sensitivity when compared to specific immunoglobulin E (sIgE) [2].

Delving into the urban context, Rhee et al. investigated the prevalence of allergies among urban adolescents and their correlation with asthma morbidity [3]. Asthma morbidities, especially those connected to allergies such as pest allergies (cockroach and mouse), have a significant association with hospital visits and other healthcare utilizations. Interestingly, those with pest allergies reported higher rates of emergency department visits, specialist consultations, and asthma exacerbations [3].

Finally, the atmospheric microbiome's role in allergies and respiratory health cannot be overstated. Elmassry et al. described the atmospheric microbiome in Lubbock, Texas, comparing the microbial content in the air during calm days and dust storm events [4]. Their research showed that while some airborne fungi remain consistently present throughout the year, dust storms notably elevate the presence of allergenic molds like Cladosporium [4]. Moreover, the study revealed how regional anthropogenic activities and the origins of air parcels significantly influence atmospheric microbiome diversity [4].

In the study by S. Yan et al., the authors explore the broader issue of urban pollution, including dust, and its impact on health [1].

Utilizing big data analysis and the Google Air Quality dataset, they propose an optimization strategy to suggest green travel routes. The study emphasizes the importance of reducing exposure to pollutants, including dust, to minimize respiratory and cardiovascular problems, chronic illnesses such as asthma, allergies, and cancer.

K. Furmańczyk et al. introduce a novel graphical model to describe the comorbidity of allergic diseases, including dust allergies [2]. The authors present two versions of the model and consider directed graphs of dependency between diseases and symptoms. This work contributes to understanding the complex interplay between different allergic diseases.

X. Wu et al. propose a novel multi-variate algorithm using triple-regression methodology to predict airborne-pollen allergy seasons, including dust allergies [3]. The three-stage regression model considers various covariates and offers customization based on individual allergy sensitivity levels. This research offers valuable insights into long-term forecasting of allergy seasons.

II. METHODODLOGY

A. *Data Collection*

This study includes the classification of dust particles present on any surface of a body. This can be possible only when concentrated and an ample amount is collected. Data is the most principal part to work on any machine learning project. A good quality of data leads to a better and perfect solution whereas data that is not fully centred and not up to the mark required for the problem leads to misguiding the model and also prevents one to find the desired result. In this research paper, data is collected using a microscope. Microscopic images are more focused and can detect micro particles of dust clearly. So a lot of dust images were collected from several different sources. Several dust particles were taken like pencil dust particles, ash, plastic dust and many more. A total of 7 classes were taken and separate data is collected for each class.

B. *Data Preparation*

i) Image Processing:

Images captured from microscope are good in visuals and size as well. Image processing steps involve resizing the images, converting images into greyscale images, and also enhancing the quality of the images. In this paper, a few or very minimal preprocessing steps were done. Images are converted to greyscale images as the neural networks and the image classification models read only greyscale images. Quality of the images is already meeting the requirement of the model so we don't have to do anything with image size.

ii) Dataset Specifications :

A total of 7 classes were declared. Each class contain a dataset of 31 images. As the data required to train the model is less, so data augmentation technique is used. Data Augmentation is a technique in which several images are created from a single image which includes change in angle of rotation, contrast, flipping of image as vertically and horizontally and increasing the height and width of the image. So, several images can be created using a single image and each image will be different in the eye of a machine learning model.

C. *Machine Learning Model*

In this research paper, both the libraries i.e. Keras and Tensorflow are used to train the dataset. Keras is an open-source high-level Neural Network library, which is written in Python is capable enough to run on Theano and TensorFlow both. It is made user-friendly, extensible, and modular for facilitating faster experimentation with deep neural networks. It not only supports Convolutional Networks and Recurrent Networks individually but also their combination. It cannot handle low-level computations, so it makes use of the backend library to resolve it. The backend library act as a high-level API wrapper for the low-level API, which lets it run on TensorFlow.

In this paper, model used for training the dataset is CNN(Convolutional Neural Network). Convolutional Neural Networks are a special type of feed-forward artificial neural network in which the connectivity pattern between its neuron is inspired by the visual cortex. The Convolutional Neural Networks, which are also called as covnets, are nothing but neural networks, sharing their parameters. The Convolutional layers encompass a set of learnable filters, such that each filter embraces small width, height as well as depth as that of the provided input volume (if the image is the input layer then probably it would be 3). Generally, a Convolutional Neural Network has three layers, which are as follows:

1. Input: If the image consists of 32 widths, 32 heights, encompassing three R, G, and B channels, then it will hold the raw pixel ([32x32x3]) values of the image.

2. Convolution: It computes the output of those neurons, which are associated with the input's local regions, such that each neuron will calculate a dot product in between weights and a small region to which they are actually linked in the input volume.

3. ReLU Layer: It is specially used to apply an activation function elementwise, like max (0,

x) thresholding at zero. It results in ([32x32x12]), which relates to an unchanged size of the volume.

4. Pooling: This layer is used to perform a downsampling operation along the spatial dimensions (width, height) that results in [16x16x12] volume.

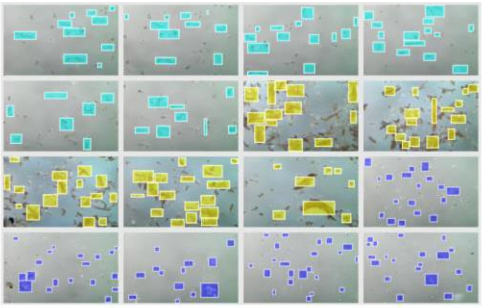

Fig 1 Various class dust detection

In this paper, CNN model is used for training of both the images i.e. original ones and the augmented images. During training 80 percent of the images are used for training while 20 percent are used for validation. Separate models are developed for original and augmented images. Both the model follows the same splitting criteria for training and validation. In both models, accuracy is obtained near 0.89, which shows the model is performing well. Output models are stored as the Keras sequential models, but to test them on the Raspberry Pi, models are converted to the Tensorflowlite model. Both the tensorflowlite models, i.e., one for the original images and one for the augmented images, are used for testing the accuracy of the model.

Based on the diversity in the acts carried out throughout each of these, four steps are narrowed down. However, during the initial testing, we ensure that the steps are different even though we could choose any step. For the purpose of gathering data, we use videos of pupils from a dancing academy. Ten students in all are chosen to participate in the data collection. We ensure that the chosen pupils are dancers at the intermediate or advanced level. This provides us with a high-quality video collection with the fewest actions/moves faults. A fixed camera placed up in front of the dancer is used to capture each pupil as they perform the moves 20 times. To make sure each video clip is correctly captured, we carefully evaluate the data that has been gathered. In a couple of films, the dancer is either positioned improperly and falls off the screen, or the routine or step is abruptly stopped. Manual removal of these clips from the dataset is done. The data gathered for each step/move following the removal of defective clips is shown in the table below.

TABLE I. NUMBER OF VIDEOS RECORDED FOR EACH SHOT

Dance Steps / Moves	**Number of Videos Recorded**
Type 1	197
Type 2	173
Type 3	188
Type 4	195

D. *Data Pre-processing*

For each stride or movement, we establish an 8-second time limit. We examine the time needed for each of the four processes before settling on this duration. We discover that the dancers can easily perform all the steps within the allotted 8 seconds. We divide the whole video recording into several clips, each containing a single dance move, as the first stage in the data pre-processing procedure. We use video editing tools to manually complete this task. Each video has the same resolution and size by default since they are all captured by the same camera. Equilibrating the video clips in terms of the number of frames they each contain is a crucial part of the data pre-processing for an LSTM model. Every tape that is captured has a variable amount of frames since every dance step is unique, and every dancer does it at a different speed. We manually sample frames from all the films and take an equal number of frames from each video to account for the varying durations of the videos.

This makes it possible for all the dancer's videos' step lengths to be the same. From all the videos, we randomly choose 160 frames. We locate the landmarks of the various body joints using the Mediapipe Pose library. Based on the video's frame width and height, the model produces the landmarks. The size of the person depends on the body size of the dancer and how close they are to the camera. Scale compensations are required due to this unpredictability. We estimate the size of the subject's body based on the Euclidean distance between the two extreme hip coordinates. We then scale the landmark points produced by the posture model using this distance.

We train the ML model using the scaled landmarks as the features. Every frame of the video undergoes a scaling procedure, and for every frame, we determine the hip distance. This is required because, during the performance, the dancer might move closer to or farther away from the camera. In reality, just the landmark points are sized, which would have the same result as scaling the entire image, as seen in the figure below, which scales the entire picture.

Fig. 1. Normalising images based on the hip size

A Python script was used to scan through each step's films and produce a Numpy binary file to contain the landmark data once the frame count equalization and scale normalization procedure was finished. The landmark data was saved in the numpy binary file as a 3D numpy array (videos, frames, and features). The Numpy array used to store the data is represented in the figure below. The Mediapipe posture model provides a total of 33 landmarks. These landmarks are scaled and normalized before being utilized as features.

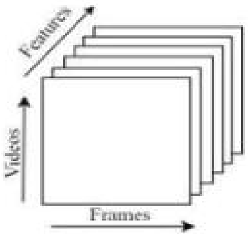

Fig. 2. Numpy array representation

All of the individual Numpy files were loaded into the RAM and combined using the 'vstack' Numpy procedure prior to training the machine learning model. The 'to categorical' function was also used to produce the necessary output labels, which were then added to the finished data itself. The data was afterward divided into training and test sets and scrambled.

E. *Machine Learning*

Since dance steps are made up of numerous frames and we wanted to identify them, we required a model that could learn the characteristics from various timesteps. Either the long short-term memory network or the recurrent neural network might be used. We chose to employ an LSTM-based model since it has significantly outperformed the RNN model when dealing with longer timesteps and the fact that the video data includes numerous time steps. We built a sequential model and trained it using the Keras Tensorflow API. We trained the model using 80% of the recorded data and tested it on the remaining 20%. Since the LSTM model needs the data to be in the format (window, frames, features), the train and test data for the LSTM model were prepared during the pre-processing stage. The sequential model developed using the Keras API is shown in the figure below. In order to prevent the model from overfitting the data, it has two dropout layers. A highly linked layer with four nodes, which stand in for the four dancing moves being identified, makes up the output layer. The model was trained using a batch size of 20 over 60 epochs.

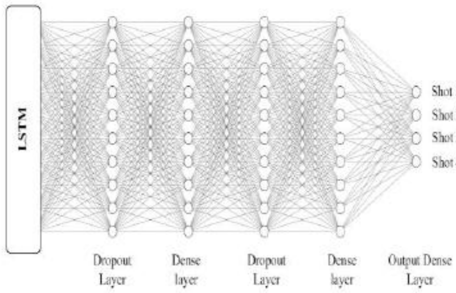

Fig. 3. LSTM model created for dance step classification

It is also feasible to test the model using real-time video, but this requires that the video data first go through all the preparation processes. To produce data that is LSTM compatible, data frames must go through the pretreatment methods outlined in the prior section. The first output from the video will be delayed by 8 seconds, or 160 frames (as per 20 frames per second), because the LSTM model predicts the dance moves based on 160 frames. As the previous 159 frames are integrated with the present frames and provided as input to the LSTM model, every successive frame will be synchronized with the live video.

III. RESULTS

Based on the diversity in the acts carried out throughout each of these, four steps were narrowed down.

Predicted Shots

Actual Shots	0	1	2	3
0	35	1	3	1
1	4	27	2	2
2	3	1	32	2
3	1	0	1	36

Fig. 4. Confusion matrix showing the model's performance

The confusion matrix developed following model testing is displayed in the figure up top. The confusion matrix shows that the model works well for the majority of the test scenarios. The model does occasionally produce false positives and false negatives.

TABLE II. MODEL PERFORMANCE METRICS

Labels	True Positive (TP)	False Positive (FP)	False Negative (FN)	Precision	Recall	F1 Score
Step 0	35	8	5	0.81	0.875	0.84
Step 1	27	2	8	0.93	0.77	0.84
Step 2	32	6	6	0.84	0.84	0.84
Step 3	36	5	2	0.87	0.94	0.90

The model has a micro F1 score of 0.86. The accuracy and recall rates at each level are all more than 80%.

The trained LSTM model can classify the steps accurately. The LSTM model took about 45 ms to create a single prediction on the 160 frames, according to a live model test. After receiving a frame, it takes the MediaPipe posture model around 20 ms to produce its landmark inference. This suggests that the trained LSTM model draws conclusions in about 25 ms. The time delay is fine as long as the LSTM model receives 160 frames.

IV. CONCLUSION

In conclusion, the LSTM model successfully categorized hip-hop dancing moves. The LSTM model figured out the patterns and connections between the various phases by preprocessing the video input and turned it into a series of feature vectors. A collection of annotated hip-hop dancing videos was used to train the model since each move was marked with the appropriate class. Using the patterns it discovered from the training data, the model reliably categorized new dance moves after it was trained. This was beneficial for various applications, such as interactive dance games or automated dancer feedback systems. Overall, the LSTM model proved to be an effective tool for categorizing hip-hop dance moves and achieved high accuracy and performance with the right training and refinement. However, there were occasional instances where the model forecasted incorrect actions. This might have been due to the manner in which video frames were sampled. When sampling the videos at 20 frames per second, certain crucial information could have been lost for some quick-moving steps.

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