Federated Learning for Air Quality Index Prediction using UAV Swarm Networks

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***Abstract*—People need to breathe, and so do other living beings, including plants and animals. It is impossible to overlook the impact of air pollution on nature, human well-being, and concerned countries' economies. Monitoring of air pollution and future predictions of air quality have lately displayed a vital concern. There is a need to predict the air quality index with high accuracy; on a real-time basis to prevent people from health issues caused by air pollution. With the help of Unmanned Aerial Vehicle's onboard sensors, we can collect air quality data easily. The paper proposes a distributed and decentralized Federated Learning approach within a UAV swarm. The accumulated data by the sensors are used as an input to the Long Short Term Memory (LSTM) model. Each UAV used its locally gathered data to train a model before transmitting the local model to the central base station. The central base station creates a master model by combining all the UAV's local model weights of the participating UAVs in the FL process and transmits it to all UAVs in the subsequent cycles. The effectiveness of the proposed model is evaluated with other machine learning models using various evaluation metrics using test data from the capital city of India, i.e., Delhi.**

Index Terms*— *Air Quality Index, Long-Short Term Memory Network, Federated Learning, Unmanned Aerial Vehicles.

I. Introduction

Air pollution has reached a harmful state with an increment in transportation facilities and large-scale industries, leading to global warming and unexpected climatic changes. The WHO's study says that the count of people dying every year due to air pollution is beyond four million. Fine particles with a diameter of 2.5 or less are majorly responsible for air pollution. Air pollution can happen naturally and because of human actions as well. The fine particles penetrate the bloodstream and cause heart and lung diseases, and in some cases, they can cause cancer. The severity of the air pollution is measured by a parameter known as Air Quality Index (AQI), which reveals the concentration of several particulate matters in the air like $PM_{2.5}$ and PM_{10}, etc. Figure 1, shows the categorization of the air quality levels [1]. Knowing the air quality value of a city, protective measures can be taken beforehand; therefore, obtaining the AQI value accurately can help us handle air pollution effectively. In recent years, the advancement of UAV technology has made it useful in numerous tasks such as aerial photography, remote sensing, autonomous navigation in an indoor environment, crop spraying, etc. [2]–[4]. Previously,

Fig. 1: AQI levels distribution as per China's Ministry of Environmental rules.

balloons, aircraft were used to measure the AQI values. These remote sensing methods have high costs and are not fully autonomous [5]–[7]. Recent development in UAV technology offers a low-cost solution where UAVs can autonomously collect data related to AQI from higher altitudes by levitating in both horizontal and vertical dimensions. In strong wind scenarios, they can stay at a fixed position in the [8]. UAVs use multiple low-cost real-time microsensors with high sensitivities for capturing data about the concentration of air pollutants [9]. Wang *et al.* [10], introduced a Convolutional Neural Network (CNN) for the prediction of AQI in a given area using high-end cameras. They used two channels to learn region-level features and stable predictions (primarily visual and semantic channels). Gao *et al.* [11], devised a UAV-aided AQI monitoring method to detect AQI value. They used the onboard camera and sensors to captures an aerial panoramic image of the environment. Caragnano *et al.* [12], used the capabilities of UAVs for automatic surveillance of larger areas. To make the model power efficient, they combined the hardware and software in an optimized way. Rohi *et. al* [13], used UAVs for air quality identification, and the excessive polluted areas are handled by lessening the air pollution by converting them to innoxious gases. Although UAVs' capabilities for AQI monitoring are assuring, however, their usage has been restricted by adequate technologies, and regulatory contingency [14].

The continuous connections between UAVs and central base stations can be affected by UAV's high mobility and high elevation. The high mobility of UAVs helps them to levitate

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at high altitudes and therefore needs constant contact with the central server [15]. However, the connection may break in between due to unexpected circumstances. Consequently, using traditional-centralized approaches for the achievement of tasks related to learning is taxing, mainly when communicating a tremendous volume of data wirelessly [16]–[18]. Moreover, the public and private firms create AQI monitoring models collaboratively by sharing data gathered via crowdsourcing. Nevertheless, the General Data Protection Regulation (GDPR) restricts data exchange between agencies to prevent data island problems. Consequently, we require to deliver an accurate AQI value while protecting privacy. Federated Learning (FL) can handle such issues, delivering distributed tasks rather than concentrating on a central server for the computation. In FL, there is no need to send any raw data to the central base server. The wireless communication in FL conditions is explored in various researches [19]. UAVs for data accumulation and training of machine learning (ML) models aggregated with FL have shown desirable results in various fields. Still, strict protocols directing data privacy hinder data sharing with independently owned UAVs. Lim *et al.* [20] aggregated FL in a UAV network to facilitate privacy-preserving collaborative ML for IoT use cases such as crowdsensing and face detection [21]. Authors in [22] optimized the FL convergence time by utilizing the capabilities of collective learning and wireless resource allocation. Donevski *et al.* [23] reviewed the issue of scheduling transmissions using FL in a sparse network of connected UAVs [24].

An air quality scheme aggregated with FL is proposed by deploying UAV swarms in a wireless connection network. The proposed system keeps track of AQI and forecasts AQI patterns from the historical time-series data. The contributions of the paper are as follows:

1) A light LSTM model is introduced with less number of parameters. The proposed model can be easily aggregated in a real-time environment for AQI data collection and predictions.
2) We build an FL framework in the UAV swarm network, enabling various firms to collaboratively observe AQI without revealing collected data to mitigate the privacy problems in AQI monitoring.
3) The proposed model's performance is compared with several ML models using a real-world time series dataset.

The organization of the paper is as follows: Section II reviews the materials and methods adopted. The proposed approach is described in Section III. Section IV evaluates the efficacy of the proposed work by telling the experimental results, and Section V delivers the conclusion.

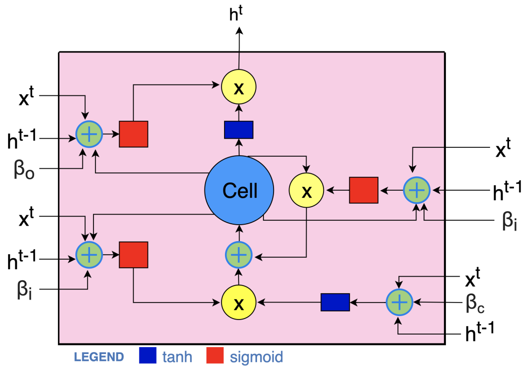


Fig. 2: A simple LSTM cell unit.

II. Material and Methods

A. Dataset

We collected the dataset[1] from the official portal of the Central Pollution Control Board of India. The dataset contains AQI values of several cities across India. Each city has AQI details on an hourly and daily basis.

B. Sensors capturing Air Pollutants

The UAV weighs toxic air particles in the air using various sensors. Air particles (NO, NO_2, NO_x, NH_3, CO, SO_2, etc.), are measured independently with separate sensors [25]. Calibration for each sensor is done fortnight. The UAV tracks time independently and gives recalibration instructions to the sensors during the calibration period.

C. LSTM networks

LSTM is similar to Recurrent Neural Networks (RNNs) that learn from sequence temporal data and offer future predictions based on the learning. Unlike RNN, LSTM's performance is not restrained by optimizations, vanishing and exploding gradient [26]. LSTM models are deployed in several advanced and challenging applications, including speech's acoustic modeling, audio/video analysis, speech synthesis, language modeling, etc. [27]. Figure 2, shows a basic LSTM cell unit. LSTM applies a "gate" arrangement to remember/forget information. The "gate" arrangement transfers the information to the subsequent layers in a selective manner. The LSTM arrangement includes three gates: one forget gate (f_g^t), one input gate (i_g^t), and one output gates (o_g^t).

III. Proposed Approach

This section provides a complete description of the proposed scheme. Firstly, the dataset is preprocessed before training the LSTM network. Post model training, the model is sent to each UAV at the initial step in the federated environment.

[1] Air Quality Data in India (2015 - 2020), website: https://www.kaggle.com/rohanrao/air-quality-data-in-india

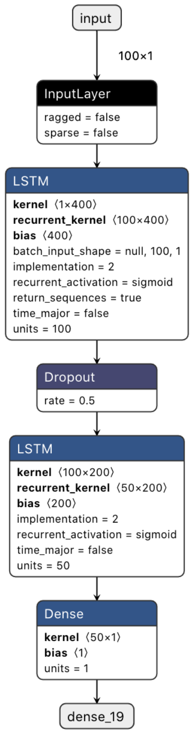


Fig. 3: Proposed LSTM Architecture.

A. *Model Construction and Training part*

1) Data Preprocessing: The dataset contains 26 different Indian cities. For training and testing of the proposed model, we picked the data values from the city *Delhi*. The dataset includes AQI values corresponding to each entry from January 2015 to July 2020. After segregating the data from the total data, we are left with 2009 entries. We then analyzed the data based on missing values and found out that ten timestamps have missing AQI values, and therefore we impute those timestamps with the mean AQI value. The unwanted columns are discarded from the dataset. Further, we divide the dataset into train and test sets having 1506 and 503 rows, respectively.

2) Model Training: The traditional ML models, such as Support Vector Machine (SVM), K-Nearest Neighbour (kNN), XGBoost, etc., are used for AQI prediction. However, these traditional ML models miss the temporal dependencies between the data. Hence, we propose a model that captures the temporal dependencies of parameters and past data. We use an LSTM network similar to RNNs to obtain precise future AQI values. Figure 3 shows the proposed model's architecture which is a supervised regression model, in which the input is a one-dimensional matrix of size equals timestep (=100) and output of the AQI prediction. In training set we have 1506 examples (T_1, T_2, T_3, ..., T_{100}, ..., T_{1506}). While training, we use T_1 to T_{100} as an input and corresponding to that we get P_{101} as an output (where P_{101} and T_{101} are predicted value actual value respectively). The loss is computed by taking the absolute difference of P_{101} and T_{101}. There are 1406 (=1506 - timestep) input and output values in the train set. Moreover, 403 values are present in the test set. For training, *'adam'* is used as an optimizer while monitoring validation, mean squared error (Val-MSE) is selected as the loss function. The model is trained and saved after each epochs using callbacks. The learning rate (initially 0.01) is decreased by the factor of 0.1 in the training stage when there is no reduction is seen in Val-MSE for successive 15 epochs. The other evaluation error metrics are mean absolute error (MAE) and mean absolute percentage error (MAPE). The training is performed by using the batch size of 64 and 100 epochs. All the parameters selected before the training process are mentioned in Table I.

TABLE I: Model training parameters.

	Value
Callbacks	ReduceLROnPlateau (factor=0.1, epsilon=0.01, patience=15)
Loss	validation MSE
Optimizer	'adam'
Metrics	'MSE', 'MAE', 'MAPE'
Batch size	64
Time step	100
Epochs	100

B. *Deploying the model on a decentralized network*

Standard or traditional ML techniques need the train data at a single place (data warehouse, database, or any central repository), as shown in Figure 4(a). They are easy to train as data is in one place. There are few drawbacks of this system: the back and forth communication (request-prediction) affects the user experience in terms of network latency, connectivity, battery life, etc. [28], [29]. Google has introduced FL, which builds a safe and robust cloud infrastructure to process data and enhance services. With the help of FL, the devices learn collectively without sending any of the device's accumulated data. This rejects the idea of storing the data in the cloud; instead, only weight and parameters will be stored in a central repository. Therefore, we choose the FL approach in our case by shifting all the training to the UAVs. In this, the data will not be sent to any central server, and therefore the training takes place on UAV itself as shown in Figure 4(b). There is an issue in the simple FL approach, as at first, there is not enough data at the UAV, so the model created will not be efficient. We initially deploy a pre-trained model (the model trained on enough data points at a central server) on all the UAVs to handle this, as shown in Figure 4(c). In Figure 4(d), the central server collects all the weights and biases from all the UAVs participating in the network. The UAVs transfer the updated model to the central server by encrypting the data packets over the wireless communication. The training data resides on the UAV, and no personal updates are reserved in the central server. In the traditional approach, we send the complete data to the central server whose size can vary from 100 MB to 1 GB of data per day. But in FL, we have to send only a few MB model parameters, thus reducing the network's latency. The model aggregates all the participating UAVs' parameters at the central server by following Algorithm 1 as shown in

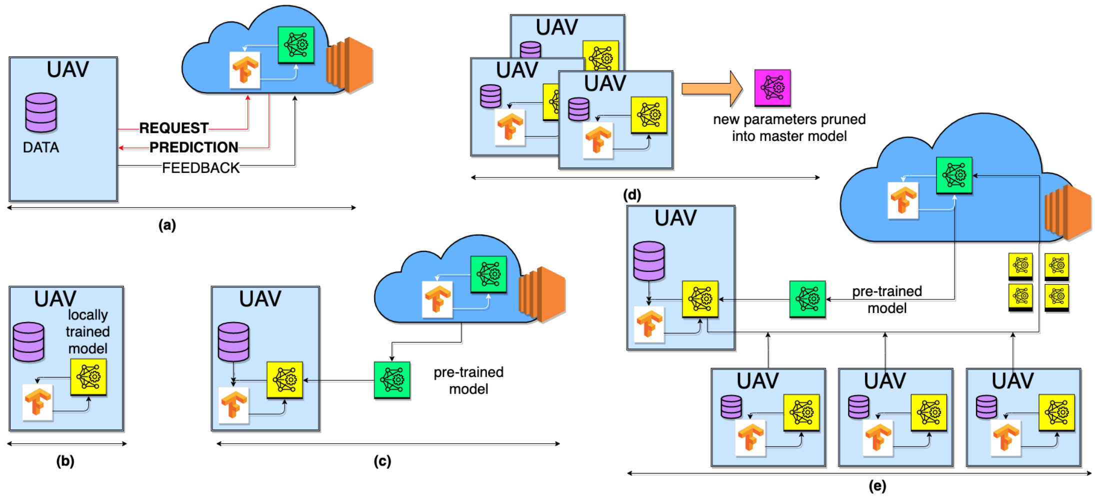


Fig. 4: Stepwise conversion of traditional/centralized approach to a federated/de-centralized approach.

Algorithm 1: FL Algorithm used in the wireless UAV swarm network.

Server side:
initialize ω_o
foreach *t in T* **do**
  U $\leftarrow$ c$\times$n
  foreach *UAV 'u' in U* **do**
    $\omega^u_{t+1} \leftarrow$ UAV_Side(u, ω_t)
  end
  $\omega_{t+1} \leftarrow \sum_{u=1}^{U} \frac{d_u}{D} \times \omega^u_{t+1}$
end
UAV side: Input $\rightarrow$ (UAV ID, master weights)
split data into 'B' batches
foreach *epoch 'e' in E and batch 'b' in B* **do**
  $\omega \leftarrow \omega$ - λ δl(ω, b)
end
return ω

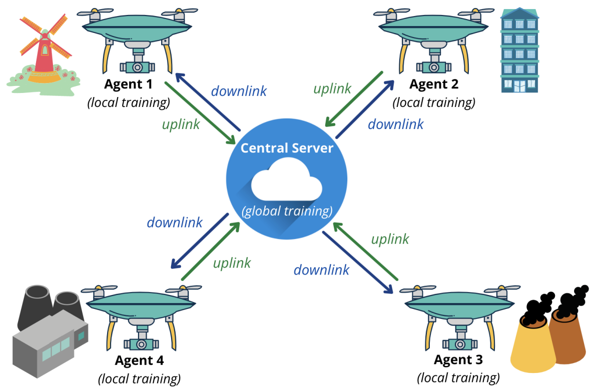


Fig. 5: Federated Network of UAV swarm.

Figure 4(e). In Algorithm 1, 'ω_o' is the initial weights trained on a significant amount of data, 'T' is the total time for the FL process, 'c' is the fraction of UAVs to be considered during the FL process. 'n' is the count of UAVs participating in the learning process, 'ω_t' is the weight at i^{th} iteration, 'd_u' is the number of data points used for training by u^{th} UAV, 'D' is the total data points used by all the UAVs in the process. The learning rate is denoted by'λ', and 'B' is the training batch size. The updated master model is then sent to all the UAVs in the next iteration.

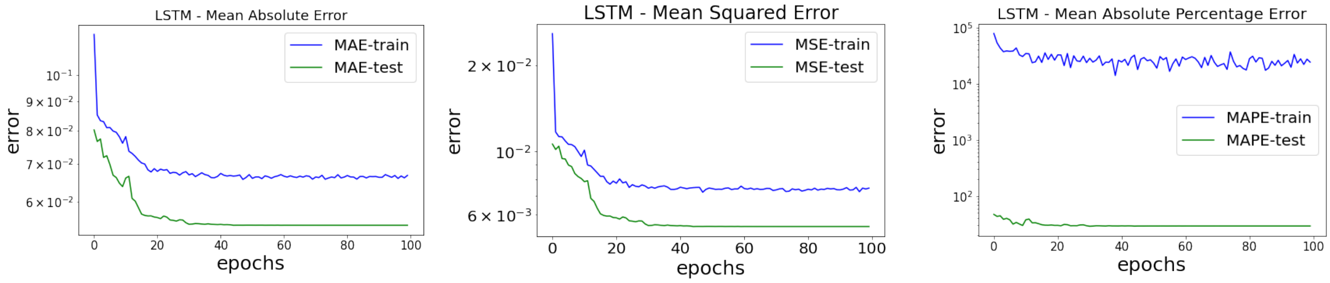
Finally, the swarm network has UAVs hovering simultaneously and communicating wirelessly with the central server. While flying, the UAVs collect the initial global model from the central server, train the model locally using FL, and finally, the AQI index is predicted for upcoming days. The UAV trains a local FL model by utilizing the accumulated data. After the training completion, with the help of the uplink channel, the local model weights are transmitted to the central base station as shown in Figure 5. The central base station combines by taking the weighted average (corresponding to the involvement of UAVs in terms of data contribution while training the local model) of all gathered models to create a global or master FL model and then transfer the global model to the UAVs via downlink. FL ensures privacy while offering lower latency and less energy consumption in parallel. The UAV can immediately use the improved model without waiting for a revised version of the global model. The central base station broadcasts information regarding the UAV spacing and the direction of movement in the swarm.

IV. Results, Discussion, and Analysis

This section evaluates the proposed scheme's performance on three-loss metrics (MSE, MAE, and MAPE). Then we plot a time-series graph of the true and predicted values. Finally, we predict the AQI for the upcoming ten days.

A. Model Evaluation

The model is assessed based on three-loss metrics MSE, MAE, and MAPE. The mentioned losses are calculated for



(a) MAE (b) MSE (c) MAPE

Fig. 6: Training and Testing error variation on the epochs (error is on log scale).

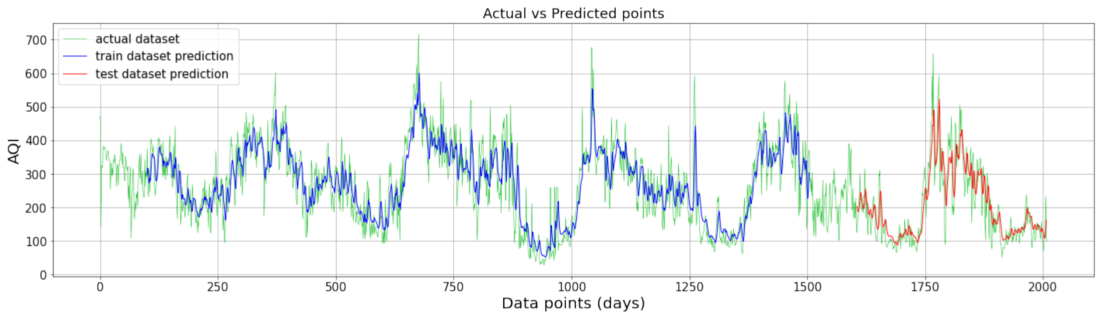


Fig. 7: Comparison between actual and predicted data points of the proposed LSTM model on both train and test set.

both training and testing datasets. The plot of each of the losses is shown in Figure 6. The train and test MAE (Figure 6a) both start decreasing rapidly at the initial epochs, and soon after 30 epochs, the graph becomes constant, and there is not much difference between the training loss and the test loss. The same trend is present for MSE (Figure 6b). For MAPE (Figure 6c), the training error is of the order of 10^5, and the test error is of the order of 10^2. There are not many fluctuations in the graph; the loss is almost constant for the complete 100 epochs training.

B. Model Prediction

The input train and test dataset are used along with the best-trained model to plot the predictions, shown in Figure 7. From Figure 7 it can be deduced that the model is credible to predict future AQI values with minimum loss. The predictions for the first 100 data points of the train and test set are missing, as these points are used for initial predictions.

C. Comparison with other ML models

The proposed model is compared using three evaluation metrics: Root Mean Square Error (RMSE), MAE, and MAPE on the test dataset containing 403 data points as shown in Table II. The recommended LSTM model offers the lowest errors (RMSE = 56.222, MAE = 41.219, MAPE = 24.184) in contrast to other ML approaches.

D. Future prediction

To predict the next ten days' AQI value using the trained model, we first select the latest 100 AQI points of the entire dataset. For the first day's AQI prediction, the proposed LSTM model will utilize these 100 data points. The predicted value of the first day and the last 99 values of the entire dataset contribute to the second predicted AQI value. Furthermore, we use the nine predicted AQI points and the last 91 data points from the entire dataset to predict the tenth day AQI value. The plot for predicting AQI values for the coming ten days is shown in Figure 8.

TABLE II: Performane evaluation of the proposed model by comparing it with the existing ML models.

Model	**RMSE**	**MAE**	**MAPE**
Support Vector Machine	61.152	49.001	32.139
KNN	82.736	68.659	48.239
Decision Tree	74.208	50.833	27.524
Artificial Neural Network	66.415	53.859	37.630
Proposed Model	56.222	41.219	24.184

All the files and code used in the proposed work are available at https://github.com/prateekchhikara/UAV_AQI_LSTM

V. Conclusion

Air holds human life; therefore, observing it, knowing its quality, and predicting the future AQI index is very important for our health. The environmental information in terms of pollutants can easily be collected using onboard sensors mounted on UAVs. UAVs can work at places and heights where it is hard for humans to get there. This paper proposed an airborne air quality sensing approach with UAV swarms. The proposed

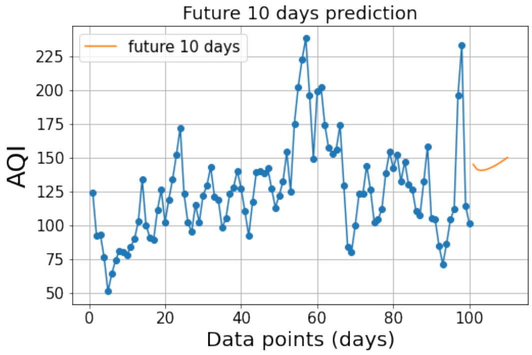


Fig. 8: Prediction of AQI for next one month.

system monitors and forecasts the AQI of a given search space. The AQI is calculated on a timely basis, and based on the data accumulated; the UAV predicts the AQI value for the coming days. The proposed scheme is aggregated with FL to make the network .decentralized. The LSTM model predicts the future AQI value with a minor error compared to other ML models. The outcomes illustrate the efficacy of the proposed scheme to predict the AQI of a given area.

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