The background of the slide is a photograph of an industrial landscape. In the foreground, there are various industrial structures, including buildings and pipes. In the middle ground, several tall smokestacks are visible, with thick white smoke rising from them. The sky is a mix of blue and orange, suggesting a sunset or sunrise. The overall tone is somewhat somber due to the industrial theme.

# Image-to-Image Deep Learning for Climate and Weather Modelling

Mentors : Zeel B Patel, Prof. Nipun Batra

Members: Aditi Agarwal, Dheeraj Yadav, Rishabh Mondal, Sandeep Desai, Saumya Karan, Suraj Borate, Suraj Jaiswal,

# Motivation



## **India Had Eighth-Worst Air Pollution in 2022: Report**

Indian cities filled 12 of the top 15 rankings of the most polluted cities in the world, the same as in last year's report.

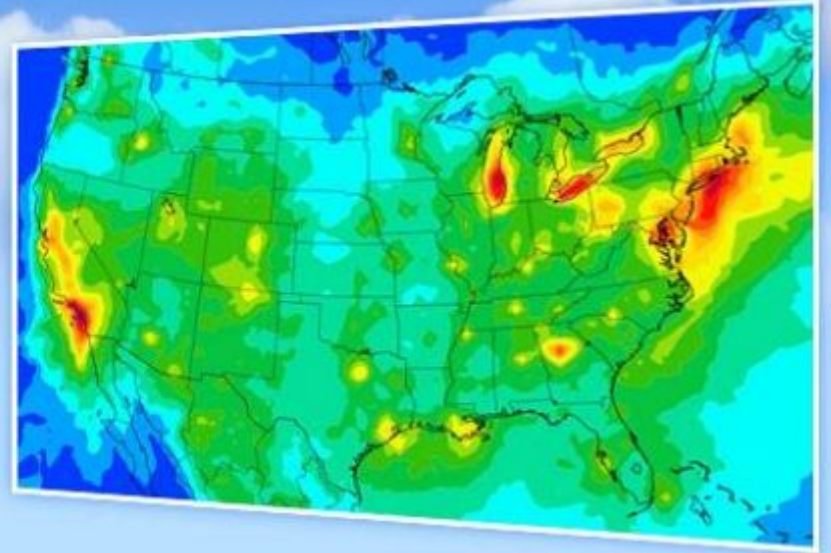
[Source](#)

## **Air pollution shortening lives by 5.3 years in India**

[Source](#)

Work: CAMx, Chemical Transport Model ([Ramboll. 2019](#))

**CAMx** Ozone  
Particulates  
Toxics



# Motivation



Example of a dispersion model for modelling air quality(CMAQ)

$$\frac{\partial c}{\partial t} = -\nabla \cdot \vec{V}c + \nabla \cdot K \nabla c + R_C + R_E + R_D$$

Time complexity for solving the equation

$$\mathcal{O}(N^{3d}) - \mathcal{O}((N+1)^{3d}) = \mathcal{O}(N^{3d-1})$$

**The compute is extremely expensive and time consuming**



# Problem Statement

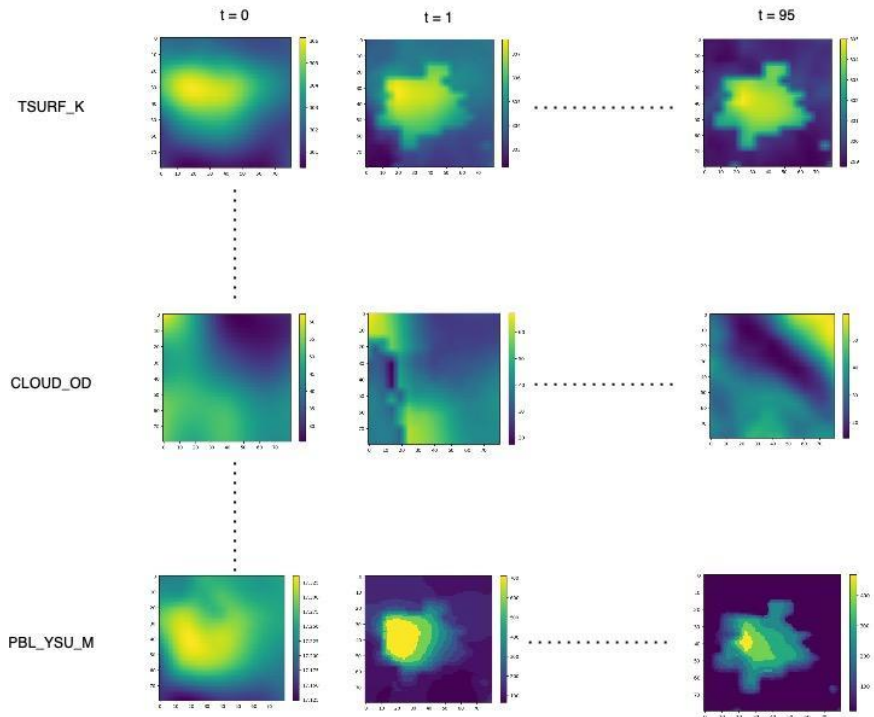
Can we eliminate existing numerical method based air quality models like CAMx by replacing them with flexible and generalizable Deep Learning based models to enhance efficiency and produce instantaneous predictions?



# Dataset Exploration

# CAMx Meteorological Dataset

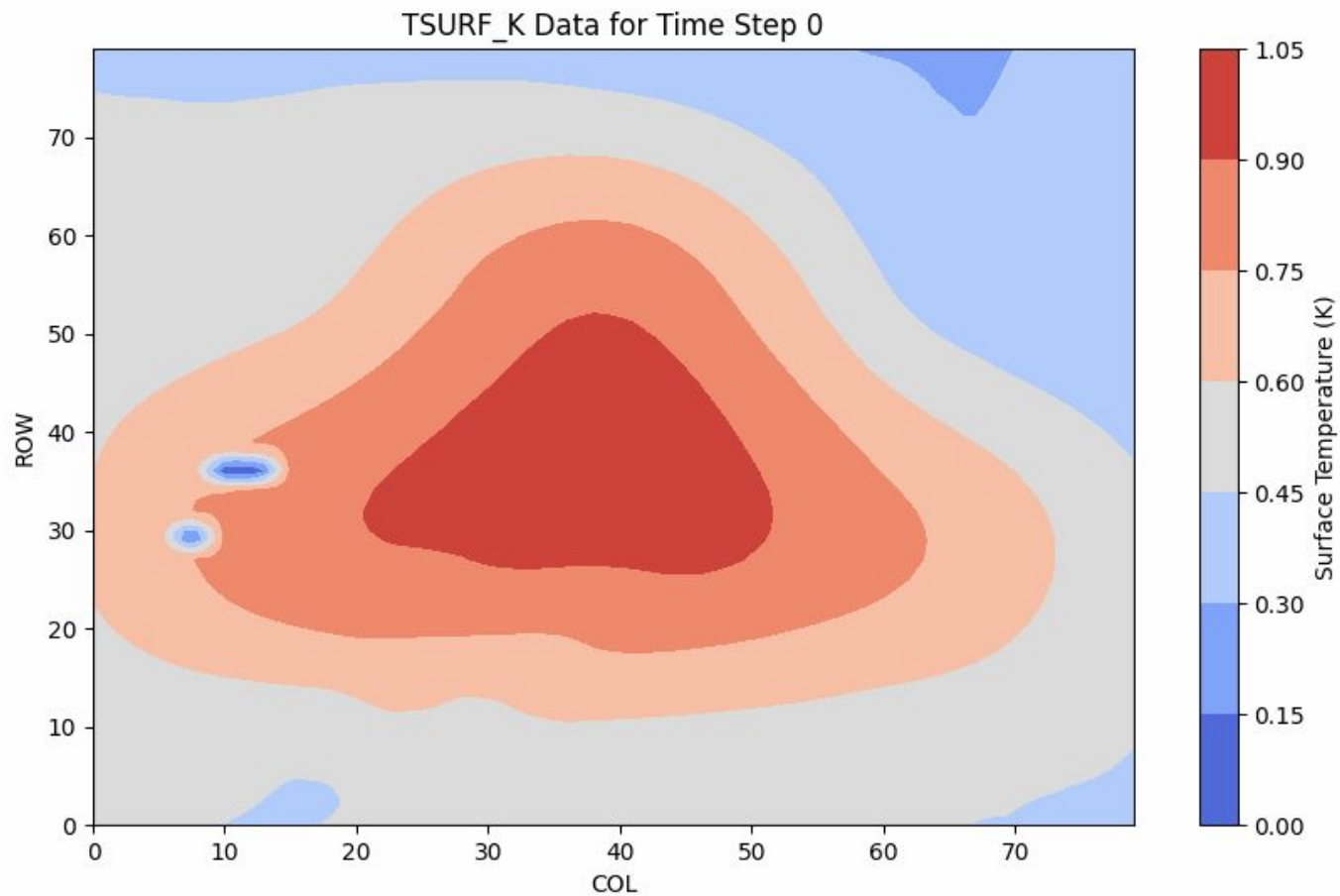
## CAMx 96hr: 14 features(Input)



14 input features  
available as hourly  
80\*80 images  
across 96 hours

Features include metrics  
for temperature,  
pressure, wind speed,  
snow cover etc.

## Normalized TSURF Data for 96 hrs

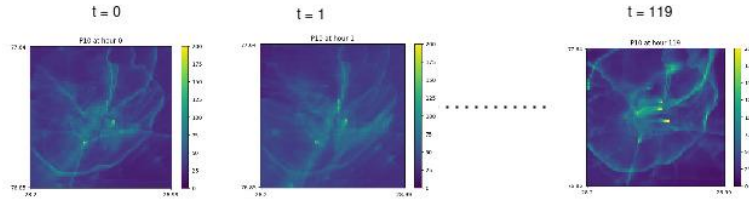




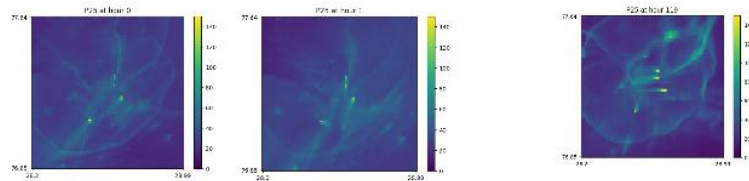
# CAMx Meteorological Dataset

## CAMx 120hr: 2 features

P10



P25



2 output features:

**P25:** Concentration of pollutant PM 2.5

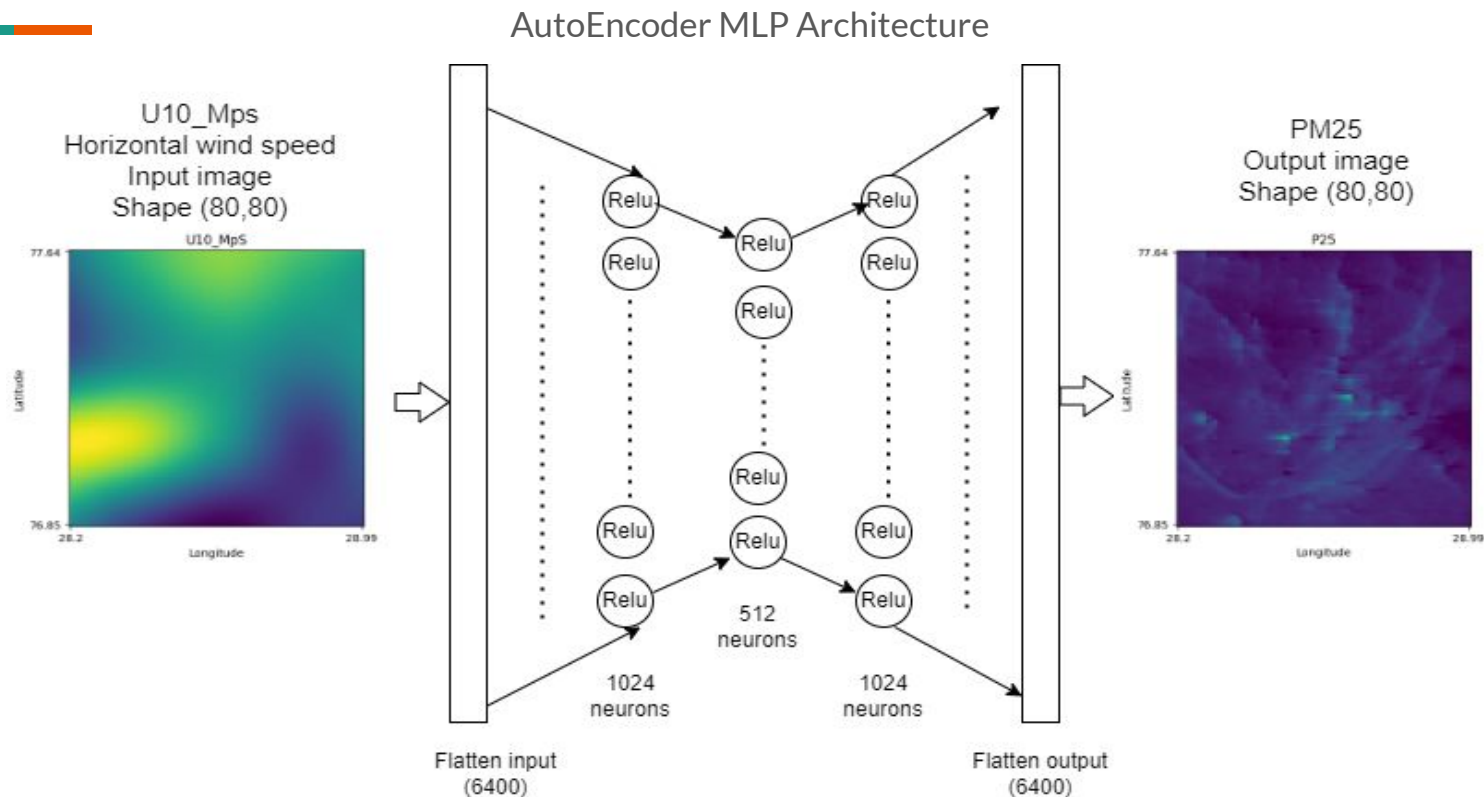
**P10:** Concentration of pollutant PM 1.0

Primary source of pollution and responsible for asthma, lung infections and premature death



# Research Questions

# RQ1: Can we train a MLP AutoEncoder which uses a single channel as input?



# Experimental Setup



Epochs	200
Optimizer	Adam
Batch Size	32
LR	0.001

# RQ1: Can we train a MLP AutoEncoder which uses a single channel as input?

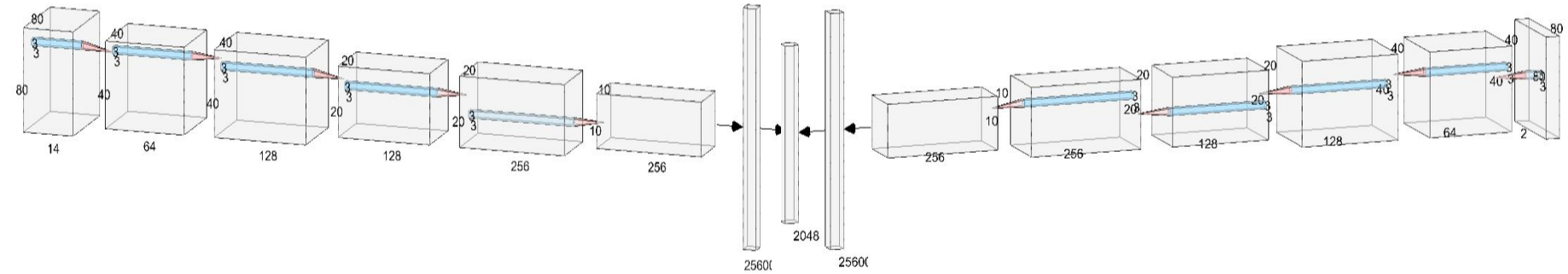


## Key Takeaways:

1. Horizontal wind speed, vertical wind speed, soil moisture content and opacity of clouds are important features for prediction of the particulate matter particles..

Input channel	MSE Loss of P10 and P25
V10_MpS	0.4
U10_MpS	0.7
SOLM_M3pM3	76.4
CLOUD_OD	95.1
PRATE_MMpH	275.4
SNOWEW_M	275.5
T2_K	275.8
CAPE	276
SNOWAGE_HR	276
PBL_WRF_M	276.2
CLDTOP_KM	276.8
PBL_YSU_M	277.9
SWSFC_WpM2	280.9
TSURF_K	296

## RQ2: Can we utilize a Convolutional Autoencoder which can take single as well as multiple input channels?



Convolutional Autoencoder Architecture  
(input 14 channels -> output 2 channels)  
Image shape: (80,80)

# RQ2: Can we utilize a Convolutional Autoencoder which can take single as well as multiple input channels?

## 2.1 Single Channel Input

Key Takeaways:

- 1. Both MLP Autoencoder and Convolutional Autoencoders have the same four features with the lowest MSE test loss.
- 2. These features are thus most important for PM concentration prediction.
- 3. Features like cloud cover and soil moisture witness a significant decrease in test loss but other features' losses remain consistent.

Input channel	Convolutional Autoencoder	MLP Autoencoder
U10_MpS	6	0.7
SOLM_M3pM3	9.8	76.4
CLOUD_OD	13.1	95.1
V10_MpS	13.2	0.4
SWSFC_WpM2	278.9	280.9
CAPE	279	276
T2_K	279	275.8
PBL_WRF_M	279.1	276.2
PRATE_MMpH	281.1	275.4
TSURF_K	282.4	296
SNOWEW_M	282.6	275.5
CLDTOP_KM	286.4	276.8
PBL_YSU_M	288.6	277.9

## RQ2: Can we utilize a Convolutional Autoencoder which can take single as well as multiple input channels?



### 2.2 All channel input

Key Takeaways:

1. Convolutional layers in the Autoencoders significantly decrease the loss

MSE Loss: **20.457**



# RQ3: Can we utilize UNet architecture across single and multiple channel inputs?

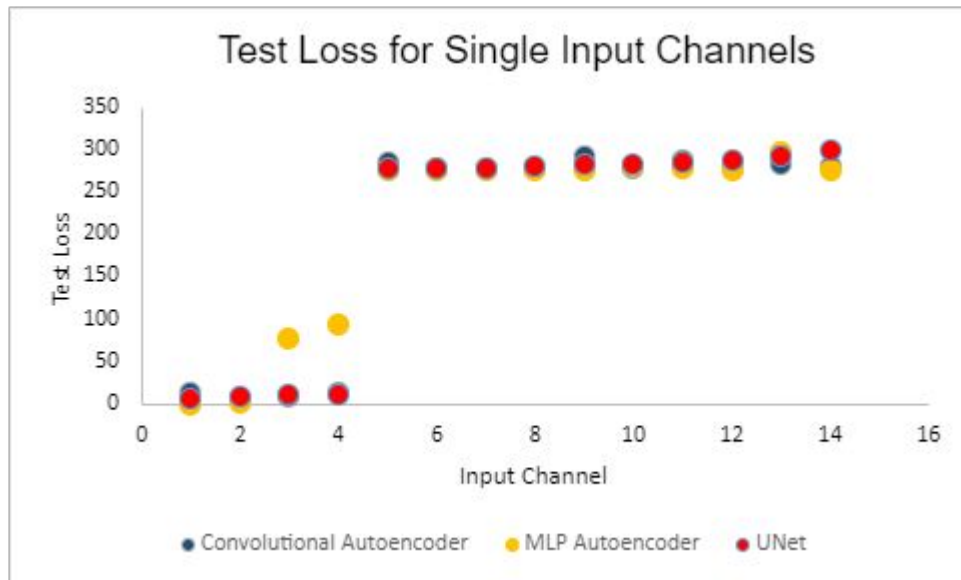


## Why?

1. To improve CNN autoencoders we cannot add more layers since it leads to degradation problem
2. UNet(Ronneberger et. al. 2015) solves this by using a similar architecture but introducing skip connections which help "remind" the network of what it was trying to learn initially.
3. Skip connections retain spatial information

# RQ3: Can we utilize UNet architecture across single and multiple channel inputs?

## 3.1 Single channel input



Input channel	Convolutional Autoencoder	MLP Autoencoder	UNet
V10_MpS	13.2	0.4	5.8
U10_MpS	6	0.7	10.1
SOLM_M3pM3	9.8	76.4	11.6
CLOUD_OD	13.1	95.1	12.4

Input Channels with the lowest test loss

# RQ3: Can we utilize UNet architecture across single and multiple channel inputs?



## 3.2 All channel input

Key Takeaways:

1. Addition of skip connections significantly reduces the MSE test loss.

CNN AE  
MSE Loss: **20.457**

UNet  
MSE Loss: **3.9575**

# RQ4: Can we use only a subset of the channels for training?

	Convolutional Autoencoder		UNet	
	All channels	Subset of Channels(4)	All channels	Subset of Channels(4)
Test Loss	20.457	<b>3.3631</b>	3.9575	<b>0.9041</b>
Training Time	14 min 3 sec (200 epochs)	2 min 40 sec (100 epochs)	13 min 15 sec (200 epochs)	3 min 17 sec (100 epochs)
Parameters	106,001,410	105,995,650	106,001,410	105,995,650

Note: In above table output channels are 2 (ie P10 and P25) across all.

## Key Takeaways:

1. Using a subset of the “most important features” significantly decreases the test loss.
2. Utilization of a partial input also helps decrease computation time as well as memory.
3. Decreases likelihood of incorporating noisy and irrelevant information.

# Conclusion



1. Thus, through a heuristic approach we are able to develop a data driven approach to model air quality.
2. Utilization of a subset of the most important CAMx inputs for training provides the best results while also significantly reducing the training time and compute.
3. Introduction of skip connections(UNet) in an existing convolution architecture significantly improves the model performance.



# Thanks