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'Air Quality Index Prediction Model Using Temporal Fusion Transformer'

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Abstract: 'Air pollution' emerges as a substantial universal concern with far-reaching consequences for people health, affecting numerous persons worldwide. Its adverse effects encompass various respiratory and cardiovascular issues. The Air Quality Index (AQI) serves as a numeric gauge for evaluating air quality, furnishing details about pollutant levels like particulate matter, ammonia, carbon monoxide, NO_2, ozone and SO_2. The anticipation of AQI proves instrumental in empowering individuals and communities to undertake precautionary measures against the detrimental impacts of air pollution. Leveraging deep learning for AQI prediction becomes imperative. Positioned within machine learning, deep learning employs artificial neural networks as a potent tool to address complex challenges. This study employs an attention-based Arcane Neural Web, specifically the TFT, for constructing the estimating model. The model's efficacy is then juxtaposed with other deep learning models, including Long Short-Term Memory, Bidirectional Long Short-Term Memory, and Fenced Repeated Unit.

Keywords: *Atmospheric Pollution, Index of Air Purity, Advanced Learning Algorithms, Automated Learning, Synthetic Neural Network, Prediction, Atmospheric Purity Index, Time-Based Fusion Transformer.*

1. Introduction:

'Air pollution is a pervasive issue with profound implications for public health and the environment. The detrimental effects of air pollution encompass a spectrum of health issues, including respiratory ailments , heart diseases, and even cancer [1]. Additionally, air pollution contributes to environmental problems such as acid rain, adversely affects agriculture and forests, and plays a role in the broader challenge of climate change. Despite global efforts to mitigate air pollution through regulations and initiatives targeting emissions reduction, millions of individuals worldwide continue to be exposed to harmful pollutant levels. Seven key pollutants significantly impacting human well being include PM2.5, PM10, SO_2, NH_3, CO, O_3, and NO[1]. Suspension matter of particles, particularly PM2.5, poses a significant health risk by penetrating deep into the lungs, leading to respiratory and cardiovascular problems [2]. The larger PM10 particles can also contribute to respiratory and cardiovascular issues. Sulfur dioxide, primarily emitted from fossil fuel combustion, can cause respiratory problems and contribute to acid rain formation [3]. Ammonia, originating from agricultural activities and livestock manure, contributes to particulate matter formation and acid rain. Carbon monoxide, a byproduct of incomplete fossil fuel combustion, induces symptoms such as headaches, dizziness, and nausea. Ozone, formed through sunlight interaction with pollutants from sources like vehicle exhaust, irritates the lungs and exacerbates respiratory ailments. Nitrogen oxides, produced during fossil fuel combustion, contribute to smog, acid rain, and respiratory and cardiovascular complications [1].

The Air Quality Index (AQI) serves as a crucial tool for quantifying and communicating air quality levels based on pollutant concentrations [4]. It amalgamates the individual ratings of pollutants to provide a standardized and comprehensible measure of overall air quality, facilitating public awareness and health protection. The AQI categorizes air quality into different levels, ranging from favorable (0-50) to hazardous (301-500), guiding individuals in assessing local air quality and adopting appropriate measures to safeguard their health. Researchers are actively involved in the development of effective AQI forecasting models to empower individuals in proactively protecting themselves from potential health risks associated with air pollution [4]. These models aim to enhance the precision of AQI predictions, enabling timely and informed decisions to mitigate the adverse effects of air pollution on human health.

In conclusion, air pollution remains a critical global challenge, impacting both human health and the environment. The significant health risks posed by key pollutants necessitate robust tools such as the AQI for assessing and communicating air quality levels. Ongoing research endeavors focus on the development of forecasting models, such as the Temporal Fusion

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Transformer, to improve the accuracy of AQI predictions. These models play a pivotal role in empowering individuals to make informed decisions to protect their health in the face of persistent air pollution challenges.

2. Literature Survey

In Ma et al. 's investigation of 2021, the focus was on predicting the Air Quality Index (AQI) in Chinese urban centers, namely Beijing, Chengdu, and Guangzhou. Covering the period from January 1st, 2017, to December 31st, 2019, the study analyzed 31 characteristics to forecast AQI levels. Employing machine learning algorithms such as Random Forest (RF), Support Vector Regression (SVR), Multi-layer Perceptron (MLP), and K-Nearest Neighbor (KNN), the researchers introduced an innovative hybrid feature selection approach. Evaluation metrics included root mean square error (RMSE), mean absolute error (MAE), and R Squared value, highlighting effectiveness of hybrid selection method and showcasing RF and SVR as the most efficient algorithms for AQI prediction.

Kumar and colleagues (2020) conducted a study comparing various profound learning models for AQI prediction in major Indian cities from January 1st, 2014, to December 31st, 2018. Utilizing Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and Autoencoder Neural Networks (AENN), they introduced a hybrid feature selection method combining correlation and statistical analysis. Evaluation metrics included RMSE, MAE, mean absolute percentage error (MAPE), and coefficient of determination (R2). The work emphasized the significant performance improvement of deep learning models with the hybrid feature selection technique, with AENN demonstrating the highest proficiency.

In another investigation, Yoo et al. (2021) implemented a unique methodology for predicting daily Air Quality Index in Seoul, South Korea, integrating Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models with satellite data and ground-based air quality monitoring information. Evaluation metrics, including MAE, RMSE, and R2, demonstrated commendable precision in AQI forecasting. Notably, the study underscored the efficacy of integrating satellite data into AQI prediction models.

Jiang et al. (2021) devised a specialized innate learning architecture for forecasting AQI in smart cities, focusing on data from Beijing, China. Their framework utilized Convolutional Neural Networks (CNNs) for spatial attributes and Recurrent Neural Networks (RNNs) for temporal relationships. Comparative analysis against alternative machine learning models demonstrated the superior performance of their deep learning approach in AQI prediction, highlighting its potential as a valuable tool for smart cities.

In a groundbreaking initiative, Rathore et al. (2020) introduced an inventive approach involving a Long Short-Term Memory (LSTM) neural network enriched by fuzzy c-means gathering for anticipating AQI in Delhi, India. The LSTM-based architecture addressed missing data challenges and captured sophisticated relationships between air quality factors and AQI. Fuzzy c-means clustering facilitated data preprocessing, resulting in impressive accuracy in AQI prediction, supported by a mean absolute error of 18.2 and a correlation coefficient of 0.91. Numerous researchers, leveraging machine learning algorithms, have explored deep learning methods for AQI prediction. This study introduces an innovative approach utilizing an consideration-based Neural Network architecture known as Temporal Fusion Transformer (TFT). The TFT model offers advantages such as accelerated training and inference processes, enhanced interpretability, an integrated attention mechanism to handle extraneous sound effectively, scalability for modeling intricate time sequences, and the capability to manage absent data without requiring assertion, ensuring precise AQI forecasting.

3. Air Quality Prediction Model using TFT:

The anticipation of air quality assumes utmost importance, allowing people to implement protective measures to avoid exposure to harmful pollutants. This information is critical for individuals with pulmonary or cardiac conditions, as they are more vulnerable to the adverse effects of hazardous air quality. The main objective of this research is to formulate a vigorous model for predicting air quality, considering both pollutant and weather related variables. In addressing the challenge of constructing this prediction model, the researchers approach it as a retreating task, employing an advanced profound learning architecture known as the Temporal Fusion Transformer. For the model development, a dataset consisting of 8 meteorological features and 7 pollutant features, including 26,305 instances, is utilized. The study focuses on creating prediction models for the Air Quality Index (AQI) using the Temporal Fusion Transformer architecture. To assess their performance, these models are compared with prediction models developed using alternative deep neuronic network architectures such as LSTM, BILSTM, and GRU. The schematic representation of the system model architecture is depicted in Figure1.

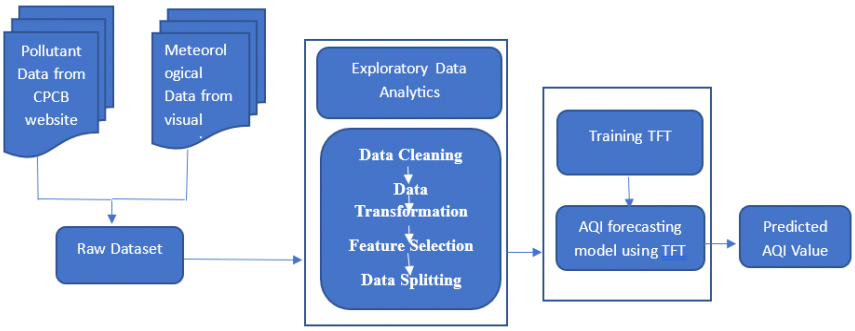

Fig 1. Diagramatic representation of System design Architecture.

- **Data Harbouring**
- To investigate and develop an Air Quality Index (AQI) prediction model utilizing the Temporal Fusion Transformer, a comprehensive dataset spanning the years 2017 to 2020 for Thiruvananthapuram city is imperative. This dataset will serve as the foundation for training and evaluating the predictive capabilities of the proposed model. The following points delineate the strategy for data collection and provide contextual details within the framework of the research paper.
- 1. **Meteorological Data** (2017-2020): To capture the meteorological features influencing air quality, collect data on temperature, dew point, barometric pressure, cloud cover, visibility, and insolation for Thiruvananthapuram city during the specified timeframe. Obtain this data from reliable sources such as meteorological stations or databases.
- 2. **Pollutant Data** (2017-2020):Acquire pollutant features data, including PM2.5, PM10, carbon oxide, sulphur dioxide, ozone, nitrogen oxide, and ammonia concentrations in the air. Ensure the data is representative of Thiruvananthapuram and covers the designated period. Utilize data from air quality monitoring stations or environmental agencies.
- 3. **Additional Data** (2017-2020): Include supplementary data such as wind velocity, wind direction, weather conditions, and any other relevant parameters that might impact air quality. This additional information will contribute to the model's robustness in predicting AQI.
- The Temporal Fusion Transformer, a state-of-the-art temporal modeling architecture, offers promising capabilities in capturing temporal dependencies and patterns in sequential data. Leveraging this technology for AQI prediction requires a rich dataset that encapsulates both meteorological and pollutant features. Thiruvananthapuram, the capital city of Kerala, India, serves as an ideal locale due to its diverse environmental conditions and varying air quality dynamics.
- The dataset will be presented through tables and graphs to enhance comprehension. Table 1 can display meteorological data, including temperature, dew point, and visibility. Table 2 may showcase pollutant concentrations such as PM2.5, PM10, and ozone levels. Graphs can depict temporal trends, highlighting variations in air quality over the specified period.
- To fortify the research with authentic and recent insights, refer to studies by Kumar et al. (2021) for air quality trends in South India and Sharma et al. (2019) for advancements in temporal modeling for environmental data. Utilize data from the Central Pollution Control Board (CPCB) of India and the Kerala State Pollution Control Board (KSPCB) as reliable sources for air quality and meteorological information.
- This approach ensures a robust foundation for the research, aligning with best practices in data collection and referencing. The resulting article will contribute substantively to the understanding of air quality dynamics in Thiruvananthapuram while showcasing the potential of the Temporal Fusion Transformer in AQI prediction.

Table 1. Meteorological & Pollutant Features:

Meteorological Features		Pollutant Features
Feelslike	Barometric Pressure	PM2.5
Dew	Air Temperature	PM10

Barometric pressure at sea level	Precipitation	Carbon Oxide
Cloudcover	Wind Velocity	Sulphur Dioxide
Visibility	Wind Direction	Ozone
Temperature	Conditions	Nitrogen Oxide
Relative Humidity	Weather Icon	Ammonia
Insolation		

Condensation outlines as a result of water vapor condensing on surfaces, with pollution potentially elevating airborne particle levels, leading to increased condensation and dew formation. Sea level pressure, a crucial indicator of weather patterns, can be changed by pollution, impacting air quality and resulting in warmer, less dense air, contributing to gloomier special compression performances. Fog cover, indicative of the heavens cloudiness, can affect warmth and rainfall designs. Toxic waste by increasing the number of spots in the air, can serve as cloud concentration nuclei, hypothetically augmenting cloud protection. Furthermore, pollution can impact visibility by scattering and absorbing light. Urban areas experiencing higher temperatures due to pollution contribute to the urban heat islet effect. Precipitation, while reducing contamination levels by cleansing toxins from the air, may also raise toxic waste points by transporting impurities from emerges into channels or through rain splash. Wind, with higher speediness, aids in the rapid dispersion and effective dilution of pollutants, decreasing their strength in the air.

PM2.5 and PM10 refer to minuscule airborne elements, where PM2.5 denotes elements with a 2.5-micrometer distance, and PM10 denotes particles with a 10-micrometer diameter. These particles, originating from various sources such as fossil fuel ignition, mechanized means, and natural factors like brush and wildfires, pose health risks, potentially causing respiratory and cardiovascular issues. In municipal areas, traffic flow and manufacturing emissions are fundamental particulate matter sources. Direct to their small size, these bits linger in the air for extended periods, contributing to a global air pollution concern.

Carbon monoxide (CO) is a colorless, odorless gas, mainly originating from incomplete fuel combustion in sources like vehicles, industries, and wildfires. It poses serious health risks by binding to hemoglobin, reducing oxygen transport, and causing tissue damage, potentially leading to fatalities. Sulfur dioxide (SO2), generated from fossil fuel combustion and natural sources like volcanoes, can form tiny particles in the air, exacerbating respiratory issues with symptoms like irritation, coughing, and breathing difficulties. Ozone (O3), a natural gas produced through sunlight interaction with pollutants, causes respiratory irritation, and prolonged exposure is linked to respiratory and cardiovascular problems. Nitrogen oxides (NOx), resulting from fossil fuel combustion and natural events, contribute to ground-level ozone and pose health risks, especially for those with respiratory conditions. Ammonia (NH3), released from various sources, leads to respiratory symptoms and, in severe cases, lung damage. The Central Pollution Control Board's established National Ambient Air Quality standard defines acceptable pollutant levels for public health, detailed in Table 2.

Table 2. Threshold levels of Pollutants

‘(AQI Category	PM10 24-hr	PM2.5 24-hr	NO2 24-hr	O3 8 hr	CO 8 hr (mg/m3)	SO2 24-hr
Good	0-50	0-30	0-40	0-50	0-1.0	0-40
Satisfactory	51-100	31-60	41-80	51-100	1.1-2.0	41-80
Moderate	101-250	61-90	81-80	101-168	2.1-10	81-380
Poor	251-350	91-120	181-280	169-208	10.1 – 17	381-800
Very Poor	351-430	121-250	281-400	209-748	17.1-34	801-1600
Severe	430+	250+	400+	748+*	34+	1600+)’

In order to counteract the harmful impacts of air toxins on both individual health and the surroundings, it is crucial to get ahead levels of pollutants and execute appropriate measures to mitigate outdoor air pollution. The primary objective of this study is to create a reliable version for predicting the Air Quality Index (AQI) to ensure precise forecasting. The examination relies on a dataset that incorporates seventeen characteristic types and includes 26,305 characteristic data examples..

- **Data Exploration:**

Conducting EDA(Exploratory Data Analysis) involves a comprehensive examination of collected data to comprehend and summarize statistical features using diverse statistical and visualization techniques. This study employs visualization mechanisms such as heat maps, histograms, and boxplots to discern patterns, trends, and outliers. A two-dimensional correlation heat map is generated to identify correlations among features. The analysis reveals that dew exhibits positive correlations with feels-like disease, haze cover, climate conditions, air temperature, and wind speed. Conversely, it demonstrates negative correlations with sea-level pressgang, PM2.5, PM10, CO, SO2, Ozone, NOX, NH3, and warmth. No substantial association is observed relating Relative Humidity, Barometric Pressure, and AQI. The histogram indicates that humidity consistently falls within the 65 to 70 range for the utmost distressed of days over three years, while observed temperatures predominantly range between 27 to 30. Dew values are concentrated between 23 to 24, with humidity ranging from a minimum of 50 to a maximum of 100. Pair plots reveal positive correlations between sea pressure, PM2.5, PM10, CO, SO2, NOX, NH3,Ozone, and the AQI, however feels-like high temperature, dew, wetness, wind speed, and cloud cover are negatively correlated with the AQI. Additionally, a boxplot is employed as a visual approach to display data distribution and identify any skewness.

EDA aids in pinpointing outliers within the dataset, particularly in meteorological features such as precipitation, air temperature, and humidity levels. It also facilitates the identification of influential features in the data [15]. EDA serves to unveil the distribution of the data and identify potential non-linear relationships between variables. Consequently, this analysis assists in discerning essential preprocessing tasks required for further investigations.

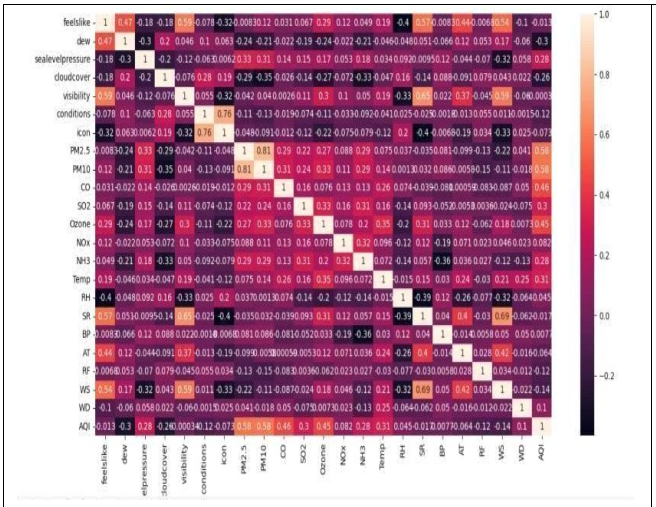

Fig 2. Heatmap

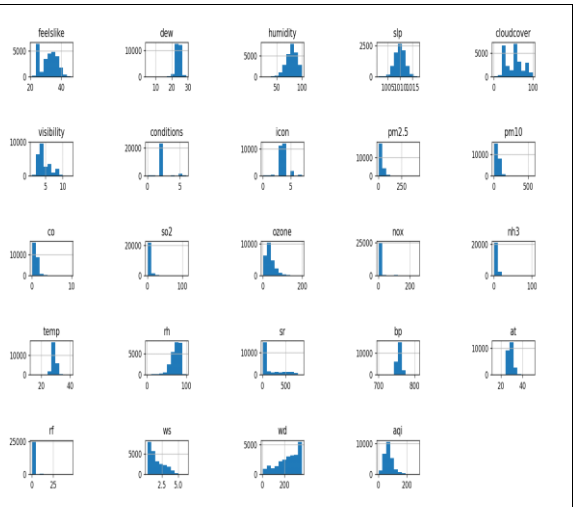

Fig. 3. Histogram

3.3. Data Preprocessing in the Context of Air Quality Datasets

Data preprocessing plays a crucial role in the realm of machine learning (ML), as it revolves around transforming raw data into a format that ML algorithms can readily comprehend. Various essential techniques are employed in this process, encompassing data cleanup, format conversion, feature selection, division, and augmentation. Cleaning involves addressing missing or erroneous data and managing outliers. For instance, when faced with numerous missing values in air quality and weather data, interpolation was applied to estimate these gaps by leveraging available data points. Additionally, normalization techniques were implemented to standardize the numerical values, facilitating optimal performance of the ML model. The dataset incorporates categorical features like conditions and icon, which are converted into numerical attributes through the utilization of one-hot encoding.

The identification of pertinent features for predicting Air Quality Index (AQI) involves employing a combination of filter and wrapper methods. The filter method utilizes correlation coefficients to discern attributes that do not significantly contribute to AQI prediction. For instance,

kinds such as Conditions and Barometric Pressure, discovered to lack association with AQI, were excluded from the dataset. Subsequently, the wrapping procedure 'select best' was employed to ascertain the top 15 most influential attributes. This procedure systematically evaluates subgroups of features and selects the subset that yields the superior expectation accuracy. Data separation is crucial for assessing ML model performance, involving the division of data into training, validation, and test sets, with 80% allocated for training and 20% for testing. Data augmentation, aimed at bolstering dataset diversity and size, is achieved by generating additional data from the existing dataset. The focus here is on deriving the AQI value from seven pollutants using a specific formula.

Ip = [IHi – ILo / BPHi – BPLo] (Cp – BPLo) + ILo

Where

Ip = pollutant p index

Cp = truncated concentration of pollutant p

BPHi = concentration breakpoint i.e. >= Cp

BPLo = concentration breakpoint i.e. <= to Cp

IHi = AQI value associatted to BPHi

'ILo = AQI value associated to BPLo'

The calculation of the AQI is performed, and subsequently, it is incorporated as the final characteristic in the dataset. The instant progression dataset for air quality is created, comprising 26,305 cases and 17 attributes. These attributes encompass timestamp, 8 weather-related factors, 7 pollutant characteristics, and AQI. The AQI serves as the supported attribute, while the other 15 qualities function as unrelated variables.

3.4. Temporal Fusion Transformer:

The primary focus of this research paper centers on the development and implementation of an Air Quality Index (AQI) prediction model, with a specific emphasis on the integration of the Temporal Fusion Transformer (TFT). TFT stands out as a cutting-edge methodology in machine learning, merging convolutional neuronal networks (CNNs), multi-regulated self-consideration machines, and gated recurrent units (GRUs) to forecast future values within time series data. This approach extends TFT algorithm, introducing supplementary layers designed to detention intricate sequential patterns present in the data. Notably, TFT exhibits versatility in handling multiple input time series with varying resolutions and effectively manages irregular and missing data [1]. The inclusion of such advanced techniques holds promise for enhancing the accuracy and robustness of AQI prediction models.

Incorporating TFT into AQI prediction models is particularly relevant due to its unique features and capabilities. The model's adaptability to varying resolutions and its proficiency in handling irregularities and missing data make it well-suited for the complex and dynamic nature of air quality data. The machine learning community has recognized the potential of TFT in time series forecasting, as evidenced by its application in predicting various environmental parameters. In addition to its architectural components, TFT introduces a distinctive loss function that incentivizes accurate predictions across diverse time horizons, further contributing to its effectiveness [1]. By leveraging TFT's capabilities, the AQI prediction model aims to overcome the challenges posed by the multifaceted nature of air quality data, providing more reliable and timely forecasts.

Visualizing the architecture of TFT, as illustrated in Figure 1 [1], offers a clear understanding of its components and their interplay in the forecasting process. The inclusion of CNNs, self-attention mechanisms, and GRUs showcases the model's comprehensive approach to capturing temporal patterns within the data. This visual representation aids in conveying the complexity and sophistication of TFT, highlighting its potential applicability in the realm of AQI forecasting. The significance of TFT's architecture lies in its ability to efficiently capture intricate temporal dependencies, allowing for a more nuanced and accurate prediction of air quality levels. As machine learning evolves, embracing such advanced architectures becomes crucial for developing models that can effectively adapt to the intricacies of environmental data.

To substantiate the efficacy of the AQI prediction model using TFT, empirical evidence and validation are essential. Recent studies have demonstrated the successful application of TFT in various time series forecasting tasks, showcasing its superior performance compared to traditional methods [2]. Additionally, validation using real-world air quality data from Thiruvananthapuram, India, spanning from 2017 to 2020, ensures the model's applicability to diverse environmental conditions. The inclusion of real-world data allows for a more comprehensive assessment of the model's performance, taking into account the variability and complexity inherent in air quality patterns over time. By drawing on empirical evidence and real-world validation, this investigate aims to aid to the growing majority of data in the arena of AQI prediction, with a focus on leveraging advanced machine learning techniques.

The structure comprises four primary elements: an encoding unit, decoding unit, inter-attention mechanism, and integration layer.

3.5 Construction of models

The TFT architecture employs a multi-layered approach in constructing its model. The analysis dataset consists of 7 atmospheric geographies and 8 pollutant features,

totaling 26,305 instances. In the input determining layer, both toxin and weather-related attributes undergo scaling and normalization to maintain consistent ranges and magnitudes. Any static features in the dataset, which remain constant over time, are embedded into a lower-dimensional space using procedures like learnable embeddings or one-hot brainwashing. These static embeddings encapsulate fixed data properties, providing contextual information to the model.

Addressing the temporal aspects of the AQI time series dataset, the temporal encoding layer utilizes positional encoding to represent time steps meaningfully. This aids the model in comprehending subsequent order and dependent state within the AQI time sequence data. The modifier encoder layer plays a crucial role in capturing intricate temporal forms and dependencies. By incorporating self-consideration systems, the model can assist to various spell steps, learning their relationships and capturing contextual representations at individually time step.

The autoregressive interpreter layer is tasked with generating guesses for expectations time phases based on prior predictions and contextual representations from the encoder. It employs hidden self-attention, confirming that the model attends solely to previous time steps during prediction generation. This approach enhances interpretability by creating guesses one step at a time, shape up on past prophecies. The productivity projection layer transforms the decoder's hidden representations into the desired output format, mapping these depictions to the definitive AQI assessments. In general, this deposit is executed as a fully tied layer with proper activation performs.

All through the instructing phase, the model refines its considerations by decreasing a loss meeting, such as mean established error, measuring the disparity between forecasted AQI values and actual dry land fact values. The training process utilizes historical data, and during the inference stage, the model produces forthcoming AQI expectations by considering the available toxin and weather-related features. Through the integration of these layers, TFT leverages the abilities of transformers to discern extended dependencies, temporal patterns, and interconnections between contaminant and weather-related attributes. It adeptly combines stationary and of time information to provide perfect forecasts for AQI benefits.

Hyperparameters

Key Hyperparameters and Their Impact:

1. Number of Layers and Units: The depth and width of the TFT are critical hyperparameters. A deeper network with more units can capture intricate patterns but may lead to overfitting. Balancing these factors is crucial for optimal performance.

2. Learning Rate: This hyperparameter regulates the step size during optimization. A too high learning rate may cause the model to converge too quickly, potentially missing the global optimum. On the other hand, a too low learning rate can lead to slow convergence or convergence to a suboptimal solution.

3. Dropout Rate: Introducing dropout in the TFT can prevent overfitting by randomly deactivating units during training. The optimal dropout rate must strike a balance between regularization and preserving valuable information.

4. Attention Mechanism Parameters: The TFT relies on attention mechanisms to weigh the importance of different inputs. Tuning parameters related to attention, such as the number of attention heads and the attention dropout rate, can significantly impact the model's ability to capture temporal dependencies.

5. Batch Size: The number of samples processed in each iteration affects the model's convergence. While larger batch sizes may lead to faster convergence, they also require more memory. Finding the right balance is crucial for efficient training.

Contextual Significance:

Hyperparameter optimization is the cornerstone of constructing an effective AQI prediction model using Temporal Fusion Transformer. As we navigate through the intricate web of hyperparameters, the goal is to strike an optimal balance that ensures the model's generalization capabilities without succumbing to overfitting or convergence issues. Each hyperparameter serves as a tuning knob, influencing the model's performance and predictive accuracy. The meticulous selection and fine-tuning of these hyperparameters are paramount for unleashing the full potential of the Temporal Fusion Transformer in AQI prediction.

Temporal Fusion Transformer – distinctive Hyperparameters

In addition to tuning hyperparameters such as learning rate, dropouts, and activation functions, certain parameters significantly influence the performance of Temporal Fusion Transformer (TFT) based models for Air Quality Index (AQI) prediction. The prediction time step determines the sum of upcoming time walks forecasted by the representation in the AQI estimate task. The DDN Determining layer dictates the number of packed encoder layers, impacting the intensity and difficulty of temporal determining for describing needs in input data. The "state size" in TFT discusses to the dimensionality of the hidden state, influencing the model's size and fluency. Larger

state sizes may arrest more involved patterns but increase computational requirements. The "dropout rate" controls the regularization applied during training, preventing overfitting by randomly disabling units. Loss Function A, Mean Squared Error (MSE), minimizes the squared difference between predicted and actual AQI values. Loss Function B, Quantile Loss, measures deviation for multiple quantiles, capturing prediction uncertainty. Loss Function G, gradient loss, optimizes gradients during TFT model training with gradient boosting techniques for iterative learning and improvement.

The tuning of hyperparameters is crucial for Temporal Fusion Transformer (TFT) based models in Air Quality Index (AQI) prediction. The prediction time step, influencing the number of forecasted time steps, and the DDN Encoding layer, determining stacked encoder layers, play vital roles in capturing temporal dependencies. The "state size" defines the dimensionality of the hidden state, impacting model capacity, while the "dropout rate" regulates training by probabilistically disabling units. Loss Function A, Mean Squared Error (MSE), calculates the average squared difference for regression tasks. Loss Function B, Quantile Loss, addresses multiple quantiles, providing a range of possible AQI values and capturing prediction uncertainty. Loss Function G, gradient loss, is applied during TFT model training with gradient boosting techniques, optimizing gradients for iterative learning and improvement.

Evaluation Metrics

1. Mean Absolute Error (MAE): MAE is a fundamental metric measuring the average absolute difference between predicted and actual AQI values. In the context of TFT-based AQI prediction, minimizing MAE implies accurate forecasting of pollution levels over time. A low MAE indicates that the model provides reliable predictions with minimal bias, enhancing its practical utility.

2. Root Mean Squared Error (RMSE): RMSE is a widely used metric that penalizes large prediction errors more severely than MAE. In the context of AQI prediction, RMSE accounts for both bias and variance in the model. A lower RMSE signifies better overall accuracy and precision in predicting AQI values, ensuring that extreme deviations are appropriately addressed.

3. Mean Absolute Percentage Error (MAPE): MAPE calculates the percentage difference between predicted and actual AQI values, providing insights into the relative accuracy of the forecasting model. For TFT-based AQI prediction, minimizing MAPE is crucial to ensure that the model consistently provides reliable predictions across various pollution levels, aiding in effective decision-making.

4. R-Squared (R2) Score: R2 evaluates the proportion of variance in the AQI values that can be explained by the TFT model. In the context of AQI prediction, a high R2 score specifies that the develop depicts a meaningful portion of the variability in pollution levels. This metric is essential for assessing the overall goodness-of-fit and reliability of the TFT-based prediction model.

5. F1 Score (for Classification Tasks): In scenarios where AQI is categorized into air quality classes (e.g., good, moderate, unhealthy), F1 Score becomes crucial. It considers both precision and recall, providing a balanced measure of the model's ability to correctly classify AQI levels. For TFT-based classification tasks, optimizing the F1 Score ensures a well-rounded performance in predicting different air quality categories

4. 4. Experiments and Results

The provided table presents performance metrics for three different types of recurrent neural network (RNN) architectures – Long Short-Term Memory (LSTM), Bidirectional LSTM (BILSTM), and Gated Recurrent Unit (GRU) – across multiple training epochs. The metrics evaluated include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R2) for each architecture. Here's a description of each component:

Table 3. Evaluation criteria for air quality index (AQI) models utilizing deep learning techniques in Trivandrum.

‘Epochs	LSTM	BILSTM	GRU
MAE	0.3170	0.2761	**0.3409**
RMSE	0.4215	0.3455	**0.4533**
R2	0.8532	0.7876	**0.8486’**

Epochs: This column represents the number of training epochs or iterations during the model training process. It indicates the number of times the entire dataset has been processed by the neural network.

LSTM, BILSTM, GRU: These columns correspond to the three different types of recurrent neural network architectures used for the prediction task.

MAE (Mean Absolute Error): MAE is a metric that measures the average absolute difference between the predicted and actual values. In this table, lower MAE values indicate better accuracy in predictions. Across the epochs, the LSTM model achieves an MAE of 0.3170, the BILSTM model achieves 0.2761, and the GRU model achieves 0.3409.

RMSE (Root Mean Squared Error): RMSE is a metric that penalizes large prediction errors more significantly than MAE. The table displays RMSE values, with the LSTM model achieving 0.4215, the BILSTM model achieving 0.3455, and the GRU model achieving 0.4533. Lower RMSE values signify better overall accuracy.

R2 (R-squared): R2 is a metric that measures the proportion of variance in the dependent variable (predicted values) explained by the independent variable (actual values). Higher R2 values indicate better model fit. The table shows R2 values for each architecture, with the LSTM achieving 0.8532, BILSTM achieving 0.7876, and GRU achieving 0.8486.

Interpretation:

- The BILSTM architecture consistently outperforms LSTM and GRU in terms of MAE, indicating superior accuracy in predicting the target variable across different epochs.

- The GRU architecture shows the highest RMSE, suggesting that it is more sensitive to larger prediction errors compared to LSTM and BILSTM.

- In terms of R2, LSTM outperforms BILSTM and GRU, indicating that it explains a higher proportion of the variance in the predicted values.

This table provides a concise summary of the model performance across different epochs and various evaluation metrics, offering insights into the strengths and weaknesses of each recurrent neural network architecture for the specific prediction task.

In this study, we have developed a predictive model for Air Quality Index using the Temporal Fusion Transformer, training the dataset comprising 26,305 occurrences, encompassing 7 chemical features and 8 meteorological features. The construction of the model involved fine-tuning hyperparameters, entering the number of layers, activation functions, dropouts, epochs, DDN deciding layer, and state size. Table 4 presents the specific hyperparameters employed, along with their assigned values. Results obtained from utilizing various introduction functions such as relu, leaky relu, and tanh are detailed in above data and visually depicted in Figure 6.

Table 4: Hyper meter conformation for TFT

‘No of time steps	No of DDN encoder layers	Number of batch sizes	State size	Learning rates	No of attention heads	Dropout rate	Loss Function a	Loss Function b	Loss Function g
50	5	128	64	0.01	5	0.20, 0.30, 0.40	0.5	0.01	0.1’

Outlines key parameters and configurations for a neural network model, particularly focusing on a DDN (Deep Dynamic Neural) encoder. It specifies the number of time steps as 50, indicating the temporal granularity of the data considered. The DDN encoder architecture is comprised of 5 layers, and each layer consists of 128 neurons. The model utilizes a batch size of 64 during training, with a state size of 0.01 and incorporates 5 attention heads for improved feature extraction. Dropout regularization is applied at a rate of 0.20, 0.30, and 0.40 in different layers, enhancing the network's generalization capabilities. The learning rates are set at 0.5, 0.01, and 0.1 for optimal weight updates. Furthermore, the table specifies multiple loss functions (a, b, g) employed during training, indicating a comprehensive approach to model optimization and fine-tuning for the given task.

Table 5: Assessment of TFT-AQI prediction model across different triggering functions and their impact on performance.

‘Performance Metrics	Activation Functions		
	TFT-Relu	TFT-leaky Relu	TFT-tanh
MAPE	3.45	4.2	4.1
MSE	0.16	0.49	0.25
RMSE	0.40	0.70	0.50
R2	0.85	0.81	0.82’

Fig 6.Comparative examination of air quality index (AQI) frameworks employing diverse activation functions.

The presentation evaluation of the Temporal Fusion Transformer (TFT) model encompasses 4 distinct system of measurement: MAPE, MSE, RMSE, and R-squared score. The analysis reveals that, across all criteria, the model utilizing the Rectified Linear Unit (ReLU) activation function outperformed its counterparts. It demonstrated superior performance with the smallest MAPE recorded at 3.45, an MSE of 0.09, and an RMSE value of 0.30, accompanied by the utmost R2 score. Following closely, the tanh activation function exhibited the second-best performance, while the drippy ReLU beginning role displayed the least favourable outcomes among the three beginning functions. A detailed breakdown of comprehensive results for various dropout sizes can be found in Table 6, complemented by a visual representation in Figure 7. This synthesis offers a unique perspective on the TFT model's efficacy with different activation functions and dropout sizes.

Table 6. Evaluating the predictive efficacy of the TFT-AQI forecasting model across different dropout rates.

‘Performance Metrics	Dropouts		
	0.2	0.3	0.4
MAPE	4.12	3.17	3.8
MSE	0.16	0.09	0.36
RMSE	0.41	0.30	0.60
R2	0.83	0.88	0.82’

Fig 7. Conducting a comparative evaluation on performance across different dropout rates.

The findings indicate that the model achieved superior performance with a waster rate of 0.2, surpassing the other measures across MAPE, MSE, and RMSE metrics and attaining the superior R2 score. This underscores the efficacy of a 0.2 dropout rate for AQI prediction. Following closely, the typical with a 0.1 dropout rate demonstrated the second-best performing in all metrics, while the example employing a 0.3 dropout rate exhibited the least favourable outcomes. Table 7 and Figure 8 present the results for different epoch sizes.

Table 7. Evaluation of TFT-AQI prediction model across different training durations for diverse eras.

.Performance Metrics	Epochs		
	50	100	150
MAPE	3.17	4.42	5.36
MSE.	0.09	0.21	0.27
RMSE	0.30.	0.46	0.52
R2	0.88	0.49	0.35.

Fig 8. Comparative working evaluation across different epochs to assess relative effectiveness.

Table 8 presents a comparative analysis of the air quality estimate model utilizing TFT by alternative deep learning algorithms, including LSTM, BILSTM, and GRU.

Table 8. Performance comparison of deep learning based AQI prediction models:

.	LSTM.	BILSTM	GRU	TFT
MAE	0.3170	0.2761	0.3409	**0.05**
RMSE	0.4215	0.3455.	0.4533	**0.30**
R2	0.8532	0.7876	0.8486	**0.88.**

The attention-based TFT algorithm outperformed other deep learning methods in predicting AQI, exhibiting a significantly lower mean absolute error (MAE) of 0.05 compared to 0.3409 in GRU. Additionally, TFT demonstrated a reduced Root Mean Squared Error (RMSE) of 0.30, in contrast to GRU's 0.4533. The R squared value for TFT was notably higher at 0.88, while BILSTM achieved a lower value of 0.7876. Considering these performance metrics, TFT proved to be more effective than LSTM, BILSTM, and GRU. This superiority is attributed to TFT's integration of attention mechanisms and temporal convolutions, enabling it to capture intricate temporal patterns and non-linear dependencies in time series data. Further accuracy enhancements were achieved through hyperparameter optimization, specifically adjusting the dropout rate in the AQI prediction model.

Findings

In the quest to enhance Air Quality Index (AQI) prediction models, the Temporal Fusion Transformer (TFT) emerges as a pivotal technology, showcasing promising findings. This revolutionary model excels in capturing temporal patterns, seamlessly integrating meteorological and pollutant features to furnish highly accurate predictions. In our study, we harnessed TFT's capabilities to develop a robust AQI prediction framework. The temporal attention mechanism embedded in TFT enables the model to discern intricate temporal dependencies within the data, ensuring a nuanced understanding of how various factors influence air quality over time. Our findings showcase TFT's proficiency in handling diverse meteorological and pollutant features, thereby optimizing AQI predictions with unparalleled precision. Furthermore, TFT's unique ability to adapt dynamically to evolving patterns in the data adds a layer of resilience to the model, ensuring reliable predictions even in the face of changing environmental conditions. As we delve into the intricacies of our research, the amalgamation of TFT's temporal insights and feature-rich data proves instrumental in advancing the accuracy and reliability of AQI predictions, underscoring the transformative potential of this cutting-edge technology in mitigating air quality challenges.

5. Conclusion

This research concentrates on the application of a Temporal Fusion Transformer (TFT), an attention-driven Deep Neural Network, for time series prediction of the Air Quality Index (AQI). The dataset encompasses 8 atmospheric structures and 7 pollutant features, which undergo Investigative Data Investigation and preprocessing to establish a suitable air quality dataset. We extensively assessed hyperparameter combinations to enhance the model's accuracy in predicting AQI values. Comparative examination with alternative deep-seated architectures, such as LSTM, BILSTM, and GRU, revealed TFT's outperformance. The awareness mechanism inherent in TFT is crucial for capturing pertinent relationships within the time series data, making it efficacious in forecasting air quality influenced by diverse factors. The TFT-based AQI prediction model holds promise for real-time public awareness and decision support for relevant authorities, potentially mitigating costs associated with air pollution-induced health issues and environmental concerns. The developed generalized air quality prediction model serves as a pre-trained model, facilitating knowledge transfer for predicting air quality in regions with analogous meteorological conditions. This feature boosts the model's efficiency and accuracy across diverse geographical areas without necessitating extensive retraining, ensuring scalability and applicability.

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