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Multi-Task Learning for Urban Air Quality Assessment with Meteorological Data

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Abstract

Urban air quality assessment consists of both categorical interpretation of pollution severity and continuous estimation of pollutant concentrations. While the Air Quality Index (AQI) categories are effective at communicating with the public, particulate matter concentrations, such as PM2.5 and PM10, are also essential to the quantitative assessment of air quality. Although there is a high degree of correspondence between the two types of assessments, they are often modeled separately. This paper proposes to use a multi-task learning (MTL) approach that can be used to assess urban air quality using data from meteorological and air-quality related tabular datasets. Specifically, under the MTL approach, the proposed model will jointly conduct AQI category classification and PM2.5/PM10 regression using a shared neural network backbone with outputs specifically designed for each task. The performance of the MTL framework will be tested on the TRAQID dataset and compared with that of single-task models using the same data-preprocessing and data-partitioning techniques. Results indicate that the MTL approach creates an integrated modeling framework that provides stable performance across both tasks, achieving an AQI classification accuracy of 93.72%, and offering insight into the trade-off between task specialization and joint representation learning.

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1. Introduction

Air pollution is one of the most significant environmental threats and one of the most prominent public health concerns. Urban areas are at risk of the combined effects of air pollution exposure over prolonged periods, resulting in increased disease rates, premature death rates, and a decrease in the overall quality of life [1]. Particulate matter (PM) is one of the most widely studied air pollutants due to its ability to penetrate the lungs and heart and its established links to serious cardiovascular disease and respiratory illness [2]. To facilitate the communication of the degree of air pollution to the general public and decision-makers at the local, state, and federal levels, urban air quality is typically expressed by the Air Quality Index (AQI), which provides discrete levels of pollution based on defined regulatory thresholds [3]. While the AQI categories are a simple way to describe air quality conditions visually, continuous monitoring of PM2.5 and PM10 concentrations is necessary to perform quantitative assessment of PM and air quality for purposes of environmental modelling, human health risk assessments, and improving air quality [4]. In conclusion, the assessment of air pollution has two components: categorical categories based on regulatory thresholds and continuous concentrations of pollutants; both components provide complementary types of information [5]. Machine learning is increasingly being used to model and predict air quality using the rapidly increasing number of environmental data sensors and other sensor technologies [6]. The efficacy of utilizing data-driven approaches to classify the Air Quality Index (AQI) and predict particulate matter concentrations has been demonstrated through previous research. However, these tasks are often addressed separately without considering that AQI Categories are determined by the concentrations of the underlying pollutants and thus have a statistical correlation to each other [7], [8]. Multi-Task Learning (MTL), provides a structured means of modelling two or more related prediction objectives at the same time (through MTL, representations that are used by multiple tasks can be learned and used at the same time, and the specific output of each task can be preserved) [9]. Common characteristics in the data being used to achieve the MTL representations can assist in achieving better performance across disparate yet correlated targets that exist together, such as environmental modelling, time-series prediction and computer vision applications [10]. The study of MTL in the context of air quality assessments will allow researchers to determine whether an MTL approach can be used to simultaneously engage in AQI category determination and particulate matter estimation through the use of the same features related to meteorological conditions and air quality [11]. One caveat is that just because the MTL approach allows two or more tasks to learn from the same representation (shared representation) does not necessarily mean that both tasks will have improved performance. Task-specific representations may lead to compromises between task specialization and generalization, particularly when there are differences in scale, noise characteristics, or optimization dynamics among the tasks. [12]. It is possible that the data used to build a model that performs well will not be representative of all instances of that task, therefore it is important to conduct empirical evaluations of models before assuming they will work on all tasks [13]. Consequently, the investigation into the use of multi-task learning for assessing urban air quality is conducted using an empirical approach. This aims to determine how to balance learned shared representations that support generalization against task-specific optimization of a model's final predictions, rather than assuming that multi-task learning is inherently superior to single-task methods. This perspective motivates a comparative analysis of single-task and multi-task formulations under identical experimental conditions to assess their respective strengths and limitations in modeling both categorical and continuous air quality indicators [15],[14].

In this paper, a multi-task learning framework is proposed for urban air quality assessment using meteorological and air-quality-related tabular data. The model jointly performs AQI category classification and PM2.5/PM10 regression through a shared neural network backbone with task-specific output heads. The approach is evaluated against corresponding single-task models under identical data splits and preprocessing conditions to assess the impact of joint learning on both categorical and continuous prediction objectives.

The remainder of this paper is organized as follows. Section 2 reviews related work on air quality prediction and multi-task learning. Section 3 describes the proposed methodology. Section 4 presents the experimental results and comparative analysis. Section 5 discusses the findings and limitations, followed by concluding remarks in Section 6.

2. Related Work

Recent studies have extensively explored machine learning approaches for predicting particulate matter concentrations in urban environments. Comparative evaluations indicate that both traditional models and deep learning architectures are capable of capturing nonlinear relationships between meteorological variables and PM2.5/PM10 levels, although reported performance is highly sensitive to data resolution, feature selection, and regional characteristics [16]. Sequence-based deep learning techniques have been developed to predict PM levels for multiple time intervals by taking into account previous behavior of pollution over time. Such approaches use encoder-decoder networks consisting of both convolutional and recurrent networks, which can provide better time-based consistency, especially relative to forecasts for the near (short- and medium-term) future [17]. The development of AQI (Air Quality Index) prediction models has been closely related to efforts to predict concentrations of air pollutants. Recent work has examined the use of machine learning for the same purpose to develop predictive models based on long-term (years) AQI and environmental factors such as meteorological conditions, finding that meteorological factors appear to play a very important role in how seasonal and climate variations affect AQI variability [18]. Many studies have also explored the potential for applying traditional statistical modeling techniques to AQI prediction over relatively long time ranges, finding that they produce quite comparable results to those from machine learning and that they continue to be sensitive to local pollution sources and meteorological conditions [19]. Thus, the context within which machines will be used is critical for successful AQI predictions and should guide the selection of AQI explanatory variables as predictors.

While research has established a close association between the level of particulate matter (PM) in the air (smaller-size particles) and the Air Quality Index (AQI), most existing studies continue to treat the prediction of the AQI and the prediction of PM separately and to model them independently of one another. This results in a duplication of the data models created for each individual task that wastes any potential benefit from shared data available from the combined use of data sources related to each modeling task [20]. The most recent comparative studies of the forecasting models for PM2.5 and PM10 have also documented that producing an optimal model specifically designed to predict an individual task produces more predictive ability than producing a generalized forecasting system that could predict multiple tasks; however, this process delivers a more complicated model and a model that will have less transferability to other similar forecast objectives [13]. By employing multi-task learning, a structured framework for creating a model based on the shared use of internal representations among related predictive objectives, and still providing task-distinction for optimizing outputs for each individual task, can provide added predictive ability and adapt to any inherent challenges in optimizing the model efficiently across multiple tasks. General research comparing different multi-task learning techniques to determine optimal methods for applying to certain types of predictive tasks has provided evidence for both benefits and difficulties associated with multi-task learning [21]. Across the field of air quality, many recent surveys have been conducted to evaluate the current level of interest in creating unified modeling frameworks, or AI models, that can predict multiple tasks and give due consideration to elements of interpretability and the adequacy of evaluation of a model as part of an Environmental Decision Support System (EDSS) before implementation [22].

Although existing studies demonstrate the effectiveness of machine learning for both AQI prediction and particulate matter estimation, most approaches address these objectives separately. As a result, the empirical trade-off between task specialization in single-task models and shared representation learning in multi-task formulations has not been systematically evaluated under identical preprocessing and data partitioning schemes.

3. Methodology

Urban air quality assessment involves both categorical interpretation of pollution levels and continuous estimation of pollutant concentrations. These objectives are related but not identical: air quality categories discretize pollution severity, whereas particulate matter concentrations quantify pollution magnitude.

Accordingly, the learning problem is formulated with two prediction tasks:

1. AQI category classification, defined as a multi-class classification problem with six mutually exclusive classes.
2. Particulate matter estimation, defined as a multivariate regression problem predicting PM2.5 and PM10 concentrations.

Rather than optimizing these objectives independently, a multi-task learning (MTL) formulation is adopted to examine whether a shared representation learned from meteorological and air-quality-related variables can support both tasks simultaneously. This formulation does not assume that joint learning necessarily improves task-specific performance; instead, it is used to evaluate the trade-off between task specialization and shared representation learning. An overview of the proposed multi-task learning framework, including data preprocessing, shared representation learning, and task-specific output heads, is illustrated in Figure 1.

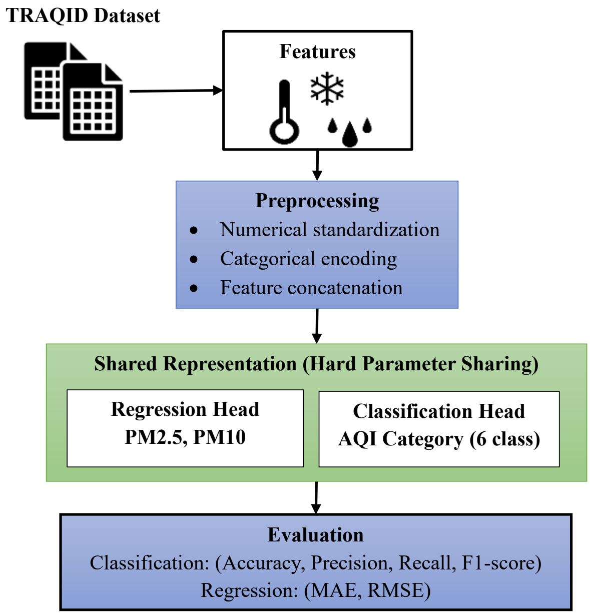

Figure 1. Architecture of the proposed multi-task learning framework for urban air quality assessment using the TRAQID dataset.

3.1 Dataset Description and Preprocessing

The TRAQID experimental data set consists of urban air quality observations, related meteorological data, and the date and time that these data were collected [23]. Each observation includes a variety of atmospheric measurements, air quality indicators (as scalar values), air quality categories (as categorical variables), and concentrations of Particulate Matter. AQI category distribution is imbalanced within the dataset as it represents a very realistic urban pollution scenario. This feature will continue to be preserved when partitioning the data, and it will also be carefully considered during the evaluation stages. Table 1 provides a summary of the types of input features and target variables that have been utilized in this research.

Table 1. Input features and target variables.

Variable	**Role**	**Type**	**Description**
Temperature	Input	Numerical	Ambient air temperature
Humidity	Input	Numerical	Relative humidity
Season	Input	Categorical	Seasonal indicator
Day_or_Night	Input	Categorical	Day vs. night indicator
AQI Category	Target	Categorical	Six air quality classes
PM2.5	Target	Numerical	Fine particulate matter
PM10	Target	Numerical	Coarse particulate matter

The scalar AQI variable acts as an input feature, while the AQI category serves as a classification target. This design references feature assisted classification, so it is clearly defined in order to eliminate any potential confusion or conflict regarding inputs/outputs.

The input variables (Temperature and Humidity) are standardized with z-score normalization to ensure that they have similar scales during the optimization phase. Categorical variables (Season and Day_or_Night) are transformed using one-hot encoding. After preprocessing, all features are concatenated into a single fixed-length input vector.

No feature selection or dimensionality reduction is applied, in order to isolate the effect of the learning formulation rather than feature engineering.

The dataset is split into training and test sets using an 80:20 ratio. Stratified sampling based on AQI category labels is applied to preserve class proportions across splits. A validation subset is further extracted from the training data to monitor generalization during training. The test set is held out and used exclusively for final performance reporting, and no samples from the test set are used during training or validation.

3.2 Model Formulation

The model being proposed uses a hard parameter sharing approach. That means it uses a single neural network that serves as a common backbone to train the same part of the network to learn representations that will be used across multiple tasks. The architecture of this backbone contains two fully connected layers (also known as dense layers) with ReLU activated functions and adds an additional, dropout layer that comes between these two layers to prevent overfitting. The goal of the shared representation is to learn about the different types of information that both the AQI category and particulate matter estimation share, such as patterns in weather that are associated with pollution. Two task-specific output heads will branch off of the shared backbone:

- A classification head, implemented as a fully connected layer with softmax activation, producing probability distributions over the six AQI categories.
- A regression head, implemented as a fully connected layer with linear activation, producing continuous estimates of PM2.5 and PM10 concentrations.

This separation allows each task to maintain task-appropriate output mappings while sharing internal representations.

A weighted sum of task-specific loss functions is minimized in order to train the model. Specifically, the following loss functions are used:

Classification Loss - Sparse Categorical Cross-Entropy; Regression Loss - Mean Squared Error of both PM2.5 and PM10 using joint computation across both outputs.

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To adjust how much each task impacts the optimization process, loss weights have been added. The classification loss has been assigned a higher weight than the regression loss to prevent significant regression errors from consuming all the computations in the optimization process. The reason for this decision stems from the discrepancy between the different numerical scales related to the two tasks and does not reflect ideas about the relative importance of each task.

Table 2. Model configuration and training parameters

Component	**Specification**
Input dimension	8 features
Shared backbone	Dense(128, ReLU) → Dropout(0.3) → Dense(64, ReLU)
Classification head	Dense(6, Softmax)
Regression head	Dense(2, Linear)
Optimizer	Adam
Classification loss	Sparse categorical cross-entropy
Regression loss	Mean squared error (MSE)
Loss weights	Classification: 1.0, Regression: 0.3
Batch size	32
Training epochs	50

Optimization is performed using the Adam optimizer with mini-batch gradient descent. Training is conducted for a fixed number of epochs, and validation metrics are monitored to assess convergence and generalization behavior.

3.3 Evaluation Metrics

The evaluation of classification performance includes precision, recall, and F1 score calculated on a per class basis. The macro-averaged F1 score will also be provided as a measure for class imbalance, while the weighted F1 score will also be reported to represent the frequencies of labels. An overall accuracy will also be the same as reports about the classification performance of the model. For the regression performance, the mean absolute error (MAE) and the root mean squared error (RMSE) will be reported for PM2.5 and PM10. These metrics capture complementary aspects of prediction error, with MAE reflecting average deviation and RMSE emphasizing larger errors.

4. Results

This section reports the quantitative results obtained from the multi-task learning model for urban air quality assessment using meteorological data. The AQI classification performance of the multi-task learning model across the six air quality categories is summarized in Table 3.

Table 3. Multi-task AQI classification performance.

AQI Category	Precision	Recall	F1-score	Support
Good	0.9818	0.3624	0.5294	149
Moderate	0.9731	0.9215	0.9466	1491
Poor	0.9336	0.8621	0.8965	457
Satisfactory	0.9279	0.9965	0.9610	2607
Severe	0.8558	0.9892	0.9177	186
Very Poor	0.9190	0.8901	0.9043	446

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Overall	—	—	0.9331	5336

The overall classification accuracy achieved by the multi-task model is 93.72%, with a macro-averaged F1-score of 0.8593 and a weighted F1-score of 0.9331.

A comparison between single-task and multi-task classification performance is reported in Table 4.The regression results of the multi-task learning model for particulate matter prediction are presented in Table 5.

A comparison between single-task and multi-task regression performance is provided in Table 6.

Table 4. Classification performance comparison between single-task and multi-task models.

Model	Accuracy (%)	Macro F1	Weighted F1
Single-Task	98.03	0.9708	0.9804
Multi-Task	93.72	0.8593	0.9331

Table 5. Multi-task regression performance for particulate matter prediction.

Pollutant	MAE (µg/m³)	RMSE (µg/m³)
PM2.5	5.26	12.22
PM10	8.83	14.72

Table 6. Regression performance comparison between single-task and multi-task models.

Pollutant	Metric	Single-Task	Multi-Task
PM2.5	MAE (µg/m³)	4.99	5.26
PM2.5	RMSE (µg/m³)	11.53	12.22
PM10	MAE (µg/m³)	8.55	8.83
PM10	RMSE (µg/m³)	14.79	14.72

Figure 2 illustrates the evolution of classification accuracy and classification loss for both training and validation sets during the training process. The classification accuracy increases progressively across epochs, while the classification loss decreases consistently for both training and validation data. The training and validation curves remain close throughout the training process, with no abrupt divergence observed between them. The final validation accuracy reaches 94.15%, accompanied by a corresponding reduction in classification loss.

Figure 3 shows the evolution of regression error metrics during training. Both MAE and MSE decrease progressively for the training and validation sets across epochs. The validation curves follow similar trends to the training curves throughout the learning process.

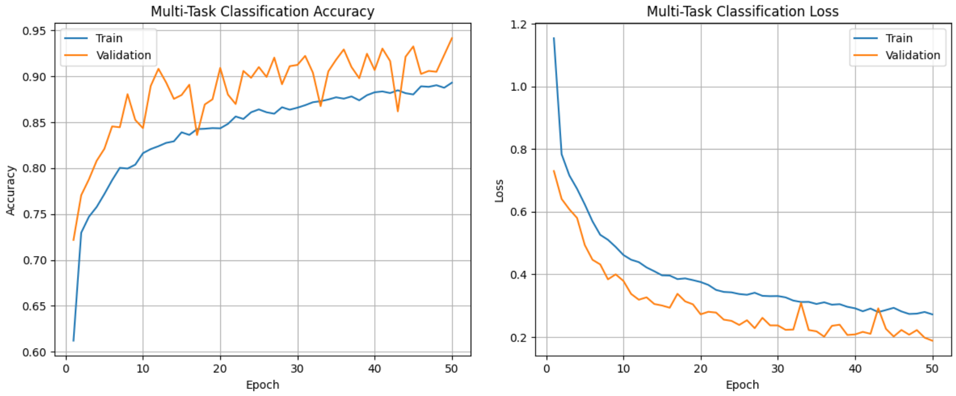

Figure 2. Training and validation curves of the multi-task learning model for classification.

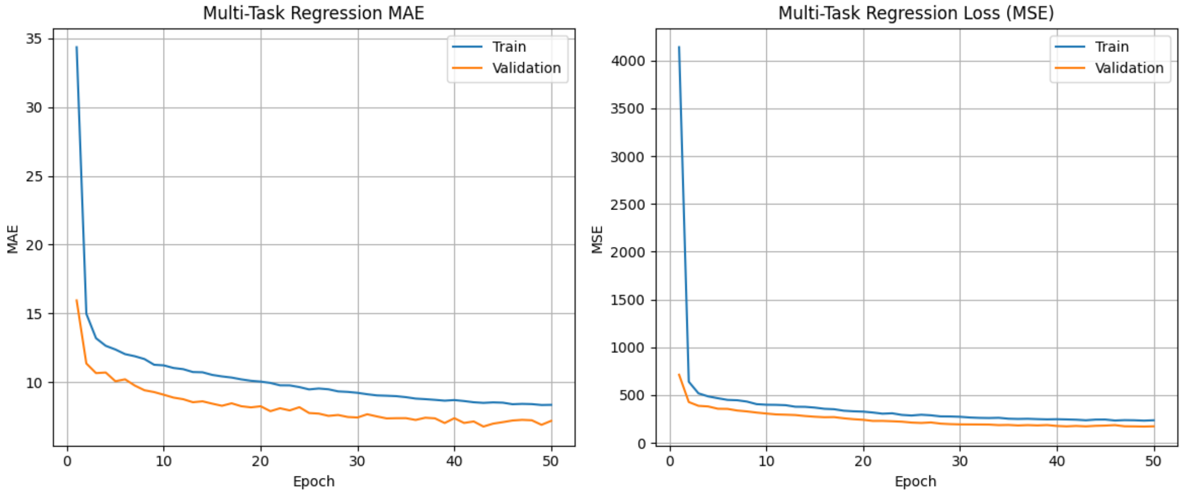

Figure 3. Training and validation curves of the multi-task learning model for regression.

5. Discussion

The purpose of this study was to determine the performance of a Multi-task Learning (MTL) approach to assess Urban Air Quality by simultaneously addressing both (AQI) category classification and estimation of particulate matter concentration. The results of our research indicate that, when evaluated in relation to each individual objective, the Multi-task MTL approach consistently provides reliable and consistent generalization performance results for both objectives.

The Multi-task MTL model achieves an overall AQI classification accuracy of 93.72%, and a weighted F1-score of 0.9331. This demonstrates a high degree of reliability for dominant classes. However, it was determined that class-level performance is variable.

Specifically, for the Good AQI category, Precision (0.98) is very high but Recall (0.36) is considerably lower. This likely indicates an imbalance in class representation and feature overlap near AQI threshold boundaries. As a result of this imbalance, Multi-task MTL prediction performances exceeded that of Single-task MTL predictors for Moderate to High levels of AQI (Exceeds 0.91).

While the accuracy for Single-task MTL classification (98.03%) was greater than that of Multi-task MTL classification (93.72%), the reduced overall accuracy of the Multi-task MTL approach demonstrates the trade-off between task-specific optimization and representational consistency across multiple objectives when using shared representations.

While the multi-task model's MAEs were greater than their single task regression counterparts (the multi-task model's MAE for PM2.5 was 5.26 µg/m³ and PM10 8.83 µg/m³) the differences were negligible. Both methods produced similar MAEs for PM10 (the single-task regression method's MAE for PM10 was 8.55 µg/m³). The differences in error therefore seem likely to arise from the shared parameters optimising errors across different predictor variables rather than optimising performance related to individual output variables.

The training curves for the regression and classification tasks were similar in their training and validation performance with no apparent divergence. This indicates that there is no overfitting occurring as would be expected when joint optimisation is performed.

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The input variables available to the models during the course of the study should be understood to represent meteorological and other contextual variables with no relation to specific sources of emissions; thus the models are capturing statistical correlations and not causal relationships. Accordingly, the performance reported for the multi-task model and single-task regression model should be interpreted as a measure of prediction capabilities for the observed conditions of the environment, and should not be interpreted as an explanation of how pollution is produced.

The adopted architecture was intentionally kept simple to ensure computational efficiency; however, future work will explore deeper architectures and advanced multi-task learning strategies.

6. Conclusions

Urban air quality monitoring with a multi-task learning (MTL) framework was studied through combined modeling of air quality category classification and particulate matter concentration using associated meteorological and air quality data. The framework was evaluated using the TRAQID dataset and compared to single-task models using identical experimental conditions. Results showed that MTL performs well in both tasks—AQI classification accuracy of 93.72%—while providing reasonable prediction errors for PM2.5 and PM10. Although single-task models achieve higher task-specific accuracy with lower regression error, MTL provides a single framework that balances performance between tasks. Therefore, the results indicate that MTL can be used to perform integrated urban air quality monitoring for simultaneous categorical and continuous predictions. Future research will focus on adaptive loss balancing methods, incorporating interpretability methods to assess task interaction analytics, and developing an evaluation of MTL across multiple cities for generalizability verification.

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