Electrical Engineering Department

Chemical Gas Classification using Transfer Learning

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Introduction

A common assumption in machine learning (ML), particularly for deep neural networks (DNNs) is that datasets must contain millions of observations for a model to generalize well. However, datasets are often too small and have dissimilar label distributions to make such generalizations. Transfer learning (TL) can be used to transfer learned features from a source dataset to a target dataset, using pre-trained models. Traditionally applied to image datasets, transfer learning has not been investigated extensively for time-series classification. This project is an attempt to fill gaps in the domain of transfer learning for classification of chemical gas sensor data.

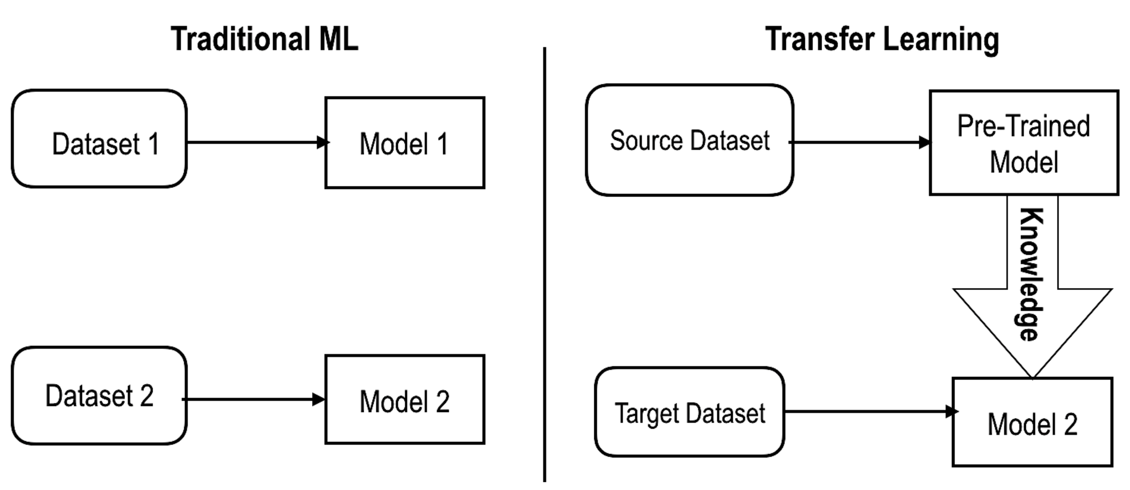

Figure 1. Traditional ML and Transfer Learning

Methodology

Data Exploration

Transfer learning can be described as the process of adopting learned features from pre-trained networks and using them as important starting points for new models. The source dataset used to develop a pre-trained network, 'Temperature Modulation' [1], consists of 4 million observations. The goal is to develop a classifier that can detect the presence of carbon monoxide (CO) in a dynamic gas mixture. The task of the classifier is challenging, since the data is time-series and also, CO is present is low concentrations while the humidity levels are uncontrolled. The experimental setup for extracting metal oxide sensor values is shown in Figure 2.

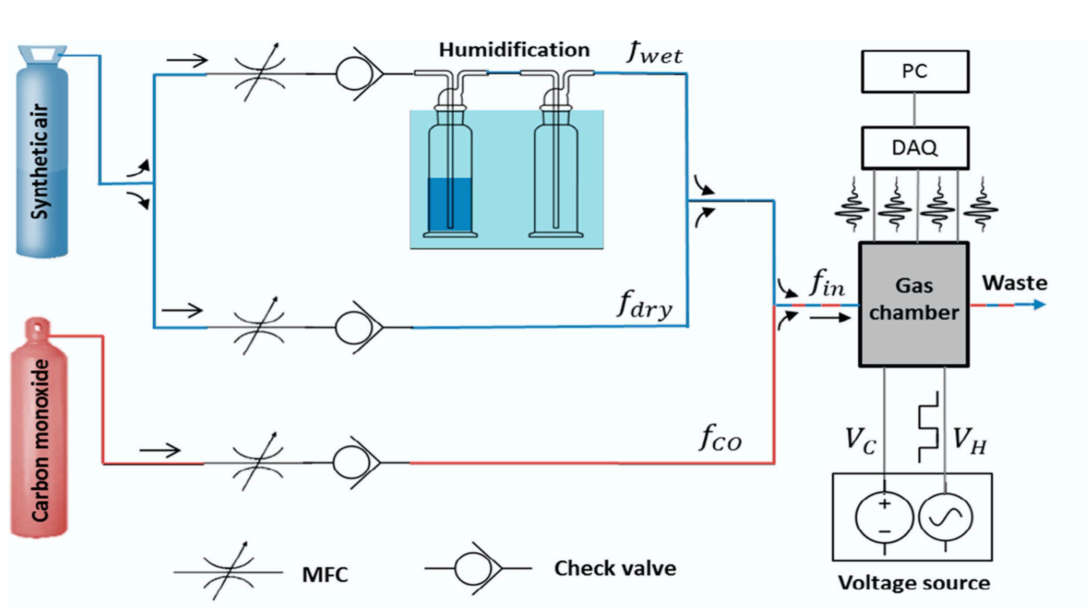

Figure 2. Experimental Setup for Dataset Generation [1]

The methodology to develop a pre-trained model on this dataset follows the training of a DNN with multiple hidden layers and performing binary classification to detect the presence of CO in a dynamic environment. These learned weights are used in the training for smaller datasets.

Methodology

Model Architecture

A DNN with three hidden layers and varying number of neurons has been used for the pre-trained model.

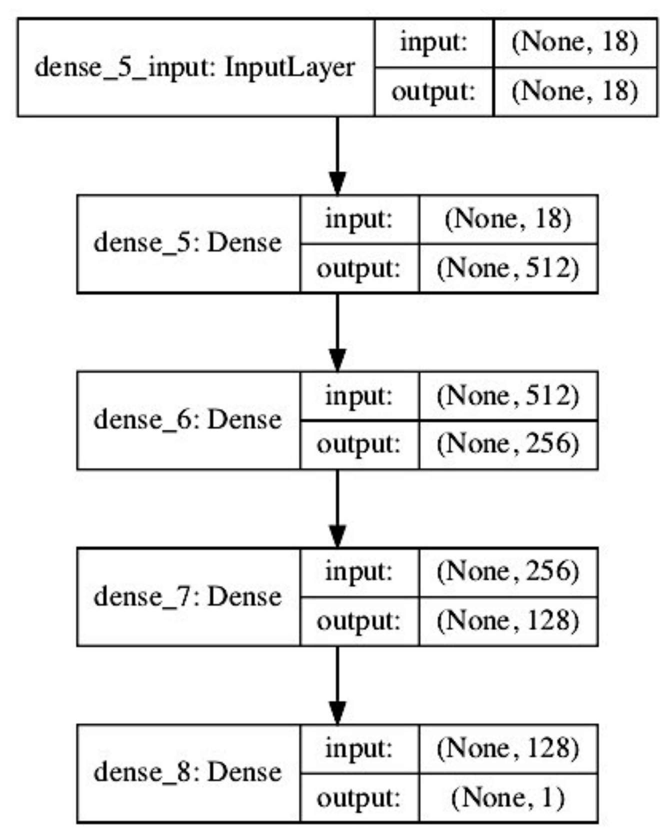

Figure 3. Multilayer Perceptron (MLP) Architecture

The Sequential model uses an input layer with 18 features and each of these features are metal oxide sensor measurements .The input and the hidden layers have a ReLU activation function and the output layer has a sigmoid function which is suitable for binary classification. This activation function generates probabilities of an input value belonging to a certain class. Since these datasets are time-series, random sampling or shuffling cannot be performed and this presents an additional challenge while performing binary classification.The dataset is preprocessed and the model is trained for 50 epochs so that it can converge to a high training accuracy. To understand the effectiveness of transfer learning, all three datasets have been used in the training of standalone models using the architecture shown in Figure 3.

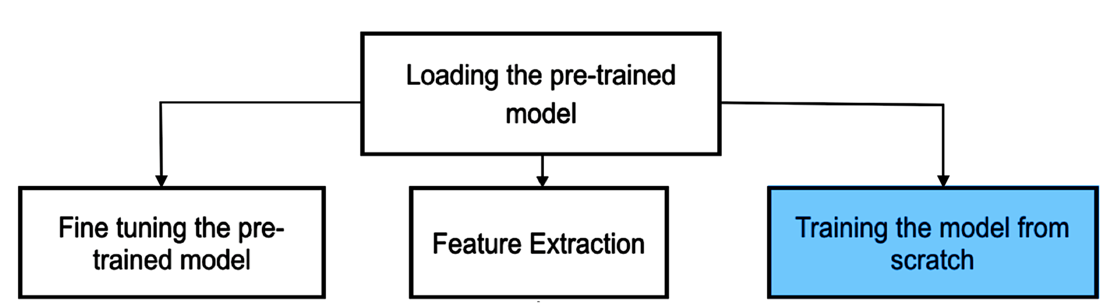

Figure 4. Transfer Learning Methods

Once the source network is trained, the learned features are saved and target dataset features are normalized and resampled for transfer learning. Conventionally, transfer learning is performed using one of the three methods shown in Figure 4. Feature extraction involves using the pre-trained network for the sole purpose of extracting valuable feature information and fine tuning involves unfreezing selected model layers and training the new network using a low learning rate. This project has utilized the method of unfreezing the entire pre-trained model. The target models also perform binary classification while predicting whether or not a target gas such as Ethylene is present at a particular time. Since both the datasets are similar in their predictive actions, transfer learning works well in transferring learned weights to the target datasets.

Analysis and Results

Results based on the models trained have been divided into two parts. Initially, all datasets have standalone models trained on them and for comparison, target datasets have transfer learning applied to them. Based on two separate results, an effective assessment can be made about the true impact of transfer learning.

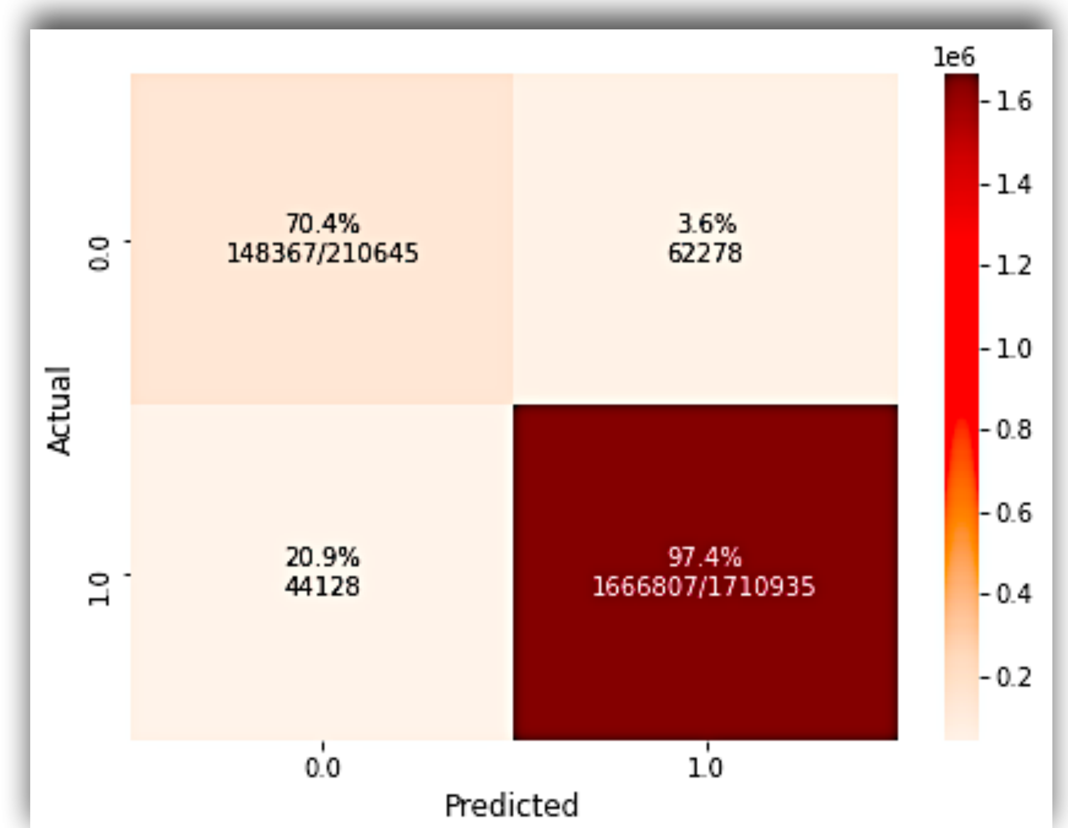

Figure 5. Performance of the Source Model

Learned features from this model are used in the training of the target models that have a new classifier replacing the last layer.

Dataset	Accuracy	Precision [0,1]	Recall [0,1]	Cohen's kappa Score
Dataset 1 [1]	0.96	0.83, 0.98	0.81, 0.98	0.8
Dataset 2 [2] (Standalone)	0.39	0.76, 0.02	0.44, 0.09	-0.21
Dataset 2 (TL)	**0.45**	**0.88, 0.1**	0.44, **0.5**	-0.02
Dataset 3 [3] (Standalone)	0.27	0, 0.27	0,1	0
Dataset 3 (TL)	**0.66**	**0.83, 0.58**	**0.48, 0.89**	**0.35**

Figure 6. Performance Metrics with and without Transfer Learning

The results in Figure 6 demonstrate the effectiveness of using a pre-trained model for the target datasets as opposed to training a model from scratch. The highlighted values indicate improvement in performance metrics when a pre-trained network is used. The transfer learning workflow used in this instance can be described as unfreezing the entire pre-trained model, replacing lower layers suitable to the target dataset and training the new model. From Figure 6, it is clear that the performance metrics have improved remarkably when the pre-trained network is used for binary classification, compared to the standalone models.

Since the datasets are unbalanced, test accuracy is not a reliable metric to gauge model performance. To accurately evaluate performance, other metrics such as confusion matrix, precision and recall are utilized. Cohen's kappa is a statistical metric that measures the similarity between the actual and predicted values by assigning a number between -1 and 1. The best similarity score is 1. Hence, using additional robust metrics provides a comprehensive analysis of the effectiveness of the pre-trained models.

Summary and Conclusion

This project has demonstrated the effectiveness of transfer learning for small datasets that have label imbalance and are time-series in nature. Extensive experiments were conducted on all three models to enhance classifier accuracy. Learned features using an MLP are transferred to smaller datasets to minimize training time and maximize test accuracy. Several performance metrics such as precision, recall and Cohen's kappa score have been used to determine model performance as the datasets have label imbalances. These results help us understand that transfer learning can be applied to chemical gas classification tasks with reasonable success and works best when the source and target datasets are similar in nature.

Key References

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