SO2_Emission_Prediction_from_Diesel_Engines_with_Quantum_Technolo

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1 SO2 Emission Prediction from Diesel Engines with Quantum Technology (5G)

Author: Emirhan BULUT **Date created:** 2022/11/12 **Last modified:** 2022/11/12 **Description:** A worldwide study has been conducted on the emission values of SO2 gases released from diesel engines in the world (class 1 if it has increased compared to the previous year, class 0 if there has been a decrease compared to the previous year, and class 0 for the starting years). In this research, 5G compatible quantum algorithms were designed by me. Quantum computer was used for the process. The minimum number of qubits is set for use on all computers. Finally, the same data was tested in the classical deep neural network (deep learning) network and Machine Learning algorithm (Random Forest). On the basis of test accuracy, the quantum5 algorithm was found to be more performant than all of them.

`<a target="_blank" href="https://colab.research.google.com/drive/1UAdJ-m9DFWlQWKnJNuyeRWmYexa1`

`<a target="_blank" href="https://github.com/emirhanai"><img src="https://www.tensorflow.org/ima`

2 Installing Libraries

[ ]:
```
!pip install pip install tensorflow==2.7.0
!pip install pennylane
```

[ ]:
```
!pip install pennylane-lightning[gpu]
```

[ ]:
```
!pip install pennylane-lightning[qubits]
```

3 Import Libraries

[ ]:
```
import tensorflow as tf
from tensorflow.keras.optimizers import Adam
from tensorflow import keras
from keras.models import Model
from tensorflow.keras import layers

import numpy as np
import numpy
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
import re

import pennylane as qml
from pennylane import numpy as p_np

from pennylane.templates.state_preparations import MottonenStatePreparation
from pennylane.templates.layers import StronglyEntanglingLayers
from nltk.corpus import stopwords
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
import tensorflow as tf
```

4 Data Prepare

[ ]:
```
!git clone https://github.com/emirhanai/
↪S02-Emission-Prediction-from-Diesel-Engines-with-Quantum-Technology-5G-
```

```
Cloning into 'S02-Emission-Prediction-from-Diesel-Engines-with-Quantum-
Technology-5G-'…
remote: Enumerating objects: 10, done.
remote: Counting objects: 100% (10/10), done.
remote: Compressing objects: 100% (10/10), done.
remote: Total 10 (delta 1), reused 0 (delta 0), pack-reused 0
Unpacking objects: 100% (10/10), done.
```

[ ]:
```
cd /content/
↪S02-Emission-Prediction-from-Diesel-Engines-with-Quantum-Technology-5G-
```

```
/content/S02-Emission-Prediction-from-Diesel-Engines-with-Quantum-Technology-5G-
```

[ ]:
```
X_train,X_test,y_train,y_test = numpy.load("X_train.npy"),numpy.load("X_test.
↪npy"),numpy.load("y_train.npy"),numpy.load("y_test.npy")
```

[ ]:
```
cd /content/
```

```
/content
```

5 Preparation of Quantum5

[ ]:
```
n_qubits = 2
dev = qml.device("default.qubit", wires=n_qubits)

@qml.qnode(dev)
def qnode(inputs, weights):
    qml.AngleEmbedding(inputs, wires=range(n_qubits))
    qml.BasicEntanglerLayers(weights, wires=range(n_qubits))
    return [qml.expval(qml.PauliZ(wires=i)) for i in range(n_qubits)]

n_layers = 8
weight_shapes = {"weights": (n_layers, n_qubits)}
```

[ ]:
```
clayer_1 = tf.keras.layers.Dense(1, activation="relu")

# construct the model
inputs = tf.keras.Input(shape=(1,))
x = clayer_1(inputs)
x = tf.keras.layers.Dropout(0.1)(x)

x = qml.qnn.KerasLayer(qnode, weight_shapes, output_dim=1)(x)

model = tf.keras.Model(inputs=inputs, outputs=x)
opt = tf.keras.optimizers.SGD(learning_rate=0.2)
model.compile(opt, loss="mse", metrics=["accuracy"])
```

6 Model Fitting

[ ]:
```
model_fit = model.fit(X_train, y_train, epochs=2, batch_size=256,shuffle=True,␣
↪validation_data=(X_test,y_test), verbose=2,callbacks=[keras.callbacks.
↪ModelCheckpoint("/content/model/model_{epoch}.h5")])
```

```
Epoch 1/2
1/1 - 10s - loss: 0.6494 - accuracy: 0.7473 - val_loss: 0.3424 - val_accuracy:
0.7273 - 10s/epoch - 10s/step
Epoch 2/2
```

```
1/1 - 10s - loss: 0.3125 - accuracy: 0.7473 - val_loss: 0.2480 - val_accuracy:
0.8182 - 10s/epoch - 10s/step
```

Model Evaluate for Quantum

[ ]:
```python
model.evaluate(X_test,y_test)
```

```
1/1 [==============================] - 1s 782ms/step - loss: 0.2480 - accuracy:
0.8182
```

[ ]:
```
[0.24798709154129028, 0.8181818127632141]
```

Model Summary for Quantum

[ ]:
```python
model.summary()
```

```
Model: "model_48"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_49 (InputLayer)       [(None, 1)]               0

 dense_50 (Dense)            (None, 1)                 2

 dropout_48 (Dropout)        (None, 1)                 0

 keras_layer_52 (KerasLayer)  (None, 1)                16

=================================================================
Total params: 18
Trainable params: 18
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier

ml = RandomForestClassifier()
ml.fit(X_train, y_train)
ml.score(X_test,y_test)
```

[ ]:
```
0.6363636363636364
```

[ ]:
```python
classic1 = tf.keras.layers.Dense(4,activation="relu")
classic2 = tf.keras.layers.Dense(3,activation="relu")
classic6 = tf.keras.layers.Dense(1, activation="sigmoid")

# construct the model
classic_inputs = tf.keras.Input(shape=(1,))
classic_ai = classic1(classic_inputs)
```

```
classic_ai = tf.keras.layers.Dropout(0.1)(classic_ai)
csai1, csai2, csai3, csai4 = tf.split(classic_ai, 4, axis=1)
csai1 = classic2(csai1)
classic_ai = tf.concat([csai1], axis=1)
classic_outputs = classic6(classic_ai)

classic_ai_model = tf.keras.Model(inputs=classic_inputs,␣
↪outputs=classic_outputs)
classic_opt = tf.keras.optimizers.SGD(learning_rate=0.2)
classic_ai_model.compile(classic_opt, loss="mse", metrics=["accuracy"])
```

[ ]:
```
classic_fit = classic_ai_model.fit(X_train, y_train, epochs=2, batch_size=256,␣
↪validation_data=(X_test,y_test), verbose=2,shuffle=True)
```

```
Epoch 1/2

WARNING:tensorflow:6 out of the last 15 calls to <function
Model.make_test_function.<locals>.test_function at 0x7fc8abc53d40> triggered
tf.function retracing. Tracing is expensive and the excessive number of tracings
could be due to (1) creating @tf.function repeatedly in a loop, (2) passing
tensors with different shapes, (3) passing Python objects instead of tensors.
For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has experimental_relax_shapes=True option that relaxes argument
shapes that can avoid unnecessary retracing. For (3), please refer to
https://www.tensorflow.org/guide/function#controlling_retracing and
https://www.tensorflow.org/api_docs/python/tf/function for  more details.

1/1 - 0s - loss: 0.2960 - accuracy: 0.2527 - val_loss: 0.2929 - val_accuracy:
0.1818 - 475ms/epoch - 475ms/step
Epoch 2/2
1/1 - 0s - loss: 0.2842 - accuracy: 0.2967 - val_loss: 0.2804 - val_accuracy:
0.1818 - 24ms/epoch - 24ms/step
```

[ ]:
```
classic_ai_model.evaluate(X_test,y_test)
```

```
1/1 [==============================] - 0s 20ms/step - loss: 0.2423 - accuracy:
0.7273
```

[ ]: [0.24225696921348572, 0.7272727489471436]

[ ]:
```
classic_ai_model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 1)]               0

 dense_1 (Dense)             (None, 4)                 8
```

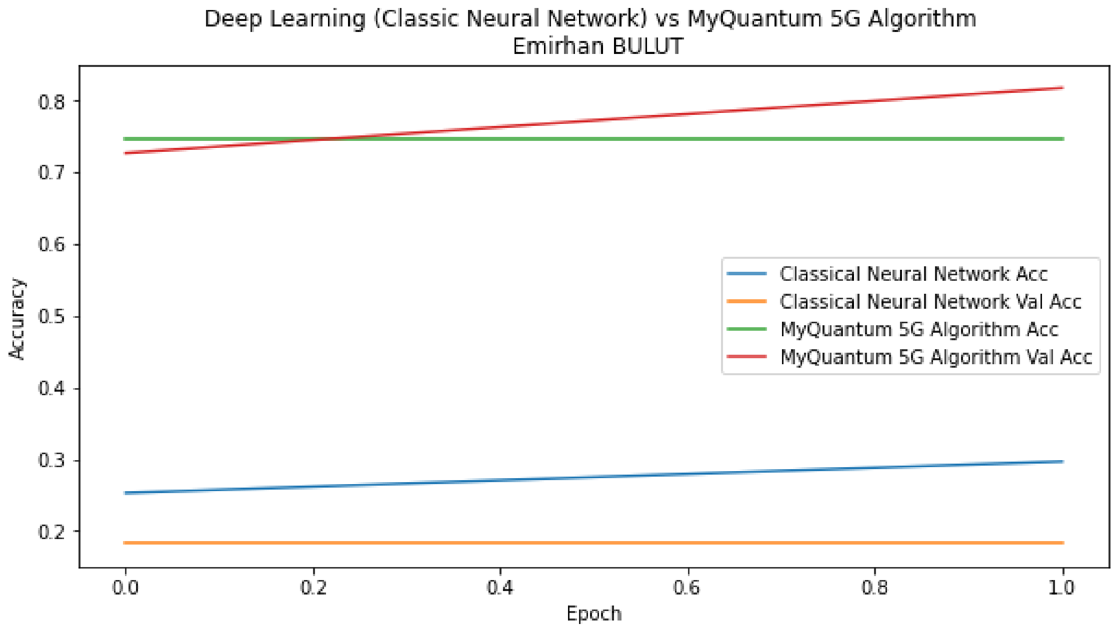
```
 dropout_1 (Dropout)         (None, 4)                 0

 tf.split (TFOpLambda)       [(None, 1),               0
                              (None, 1),
                              (None, 1),
                              (None, 1)]

 dense_2 (Dense)             (None, 3)                 6

 tf.identity (TFOpLambda)    (None, 3)                 0

 dense_3 (Dense)             (None, 1)                 4

=================================================================
Total params: 18
Trainable params: 18
Non-trainable params: 0
_________________________________________________________________
```

7 Compare performance

7.1 Deep Learning (Classic Neural Network) vs MyQuantum 5G Algorithm

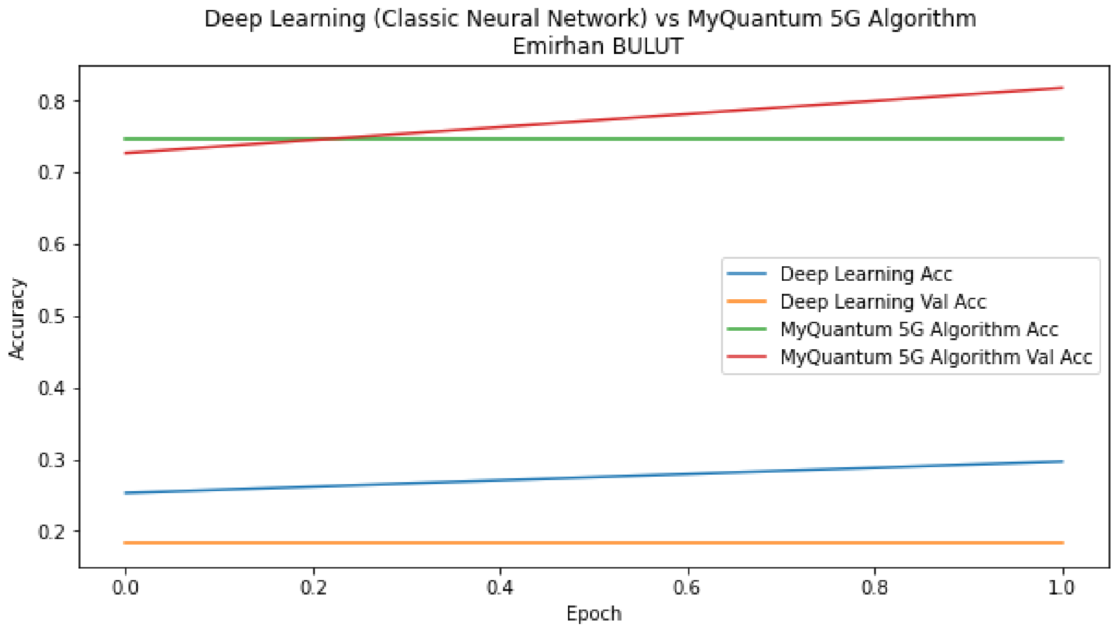
[ ]:
```
plt.figure(figsize=(10,5))
plt.plot(classic_fit.history['accuracy'], label='Classical Neural Network Acc')
plt.plot(classic_fit.history['val_accuracy'], label='Classical Neural Network␣
 ↪Val Acc')
plt.plot(model_fit.history['accuracy'], label='MyQuantum 5G Algorithm Acc')
plt.plot(model_fit.history['val_accuracy'], label='MyQuantum 5G Algorithm Val␣
 ↪Acc')
plt.title("Deep Learning (Classic Neural Network) vs MyQuantum 5G Algorithm \n␣
 ↪Emirhan BULUT")
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

[ ]:
```
<matplotlib.legend.Legend at 0x7fc930321d90>
```



[ ]:
```
plt.figure(figsize=(10,5))
plt.plot(classic_fit.history['accuracy'], label='Deep Learning Acc')
plt.plot(classic_fit.history['val_accuracy'], label='Deep Learning Val Acc')
plt.plot(model_fit.history['accuracy'], label='MyQuantum 5G Algorithm Acc')
plt.plot(model_fit.history['val_accuracy'], label='MyQuantum 5G Algorithm Val␣
↪Acc')
plt.title("Deep Learning (Classic Neural Network) vs MyQuantum 5G Algorithm \n␣
↪Emirhan BULUT")
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

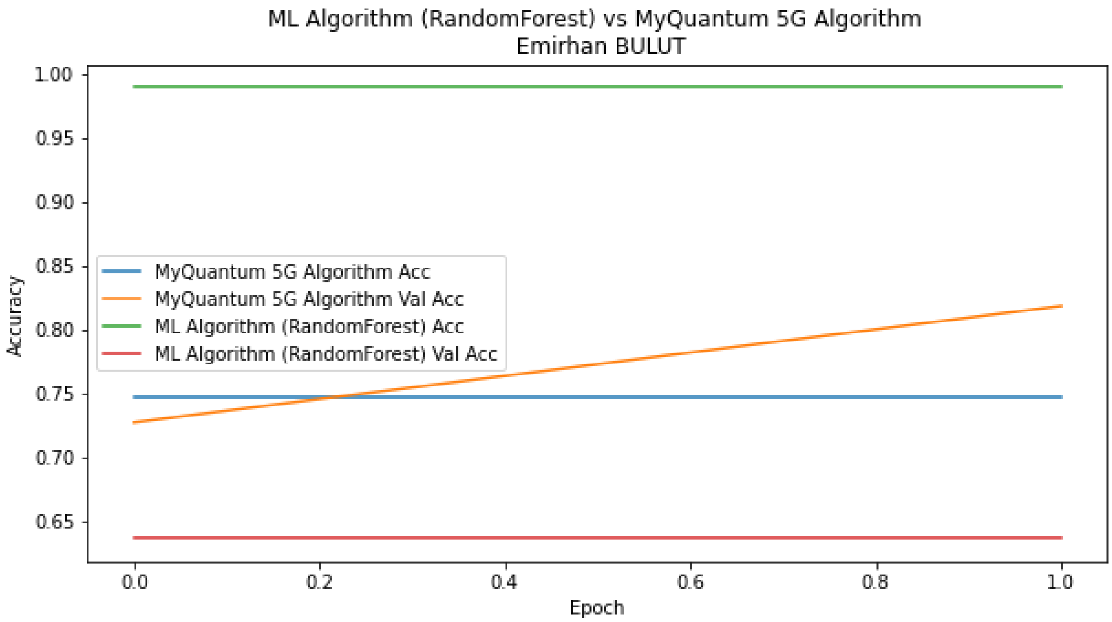
[ ]: <matplotlib.legend.Legend at 0x7fc8abe21f10>



7.2 ML Algorithm (RandomForest) vs MyQuantum 5G Algorithm

[ ]:
```
plt.figure(figsize=(10,5))
plt.plot(model_fit.history['accuracy'], label='MyQuantum 5G Algorithm Acc')
plt.plot(model_fit.history['val_accuracy'], label='MyQuantum 5G Algorithm Val␣
↪Acc')
plt.plot([ml.score(X_train,y_train),ml.score(X_train,y_train)], label='ML␣
↪Algorithm (RandomForest) Acc')
plt.plot([ml.score(X_test,y_test),ml.score(X_test,y_test)], label='ML Algorithm␣
↪(RandomForest) Val Acc')
plt.title("ML Algorithm (RandomForest) vs MyQuantum 5G Algorithm \n Emirhan␣
↪BULUT")
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

[ ]:
```
<matplotlib.legend.Legend at 0x7fc8d440dd10>
```



7.3 Classical AI Model Bytes vs Quantum 5G AI Model Bytes

[ ]:
```
#Classic AI model save
classic_ai_model.save("classicai.h5")
#Quantum 5 AI model save
model.save("quantum5g.h5")
```

[ ]:
```
import os
classic = "classicai.h5"
quantum = "quantum5g.h5"
file_stats_classic = os.stat(classic)
file_stats_quantum = os.stat(quantum)
print(f'Classic AI Model Size in Bytes is {file_stats_classic.st_size}')
print(f'Quantum 5G Model Size in Bytes is {file_stats_quantum.st_size}')
```

```
Classic AI Model Size in Bytes is 24120
Quantum 5G Model Size in Bytes is 20384
```

[ ]:
```
plt.figure(figsize=(10,5))
plt.plot([file_stats_classic.st_size,file_stats_classic.st_size],␣
 ↪label='Classic AI Model Size in Bytes')
plt.plot([file_stats_quantum.st_size,file_stats_quantum.st_size],␣
 ↪label='Quantum 5G Model Size in Bytes')
plt.title("Classical AI Model Bytes vs Quantum 5G AI Model Bytes \n Emirhan␣
 ↪BULUT")
```

```
plt.xlabel('0-1 range')
plt.ylabel('Bytes')
plt.legend()
```

[ ]: <matplotlib.legend.Legend at 0x7fc8ac152dd0>