BioGecko

Vol 12 Issue 02 2023
ISSN NO: 2230-5807

A Novel Technique for recognizing Steel Industry Energy Consumption

Dr.A.Ganesan[1],Dr.P.Anand[2],Dr.L.Raja[3],Dr.A.Thankaraj[4], Dr.G.Chinnadurai[5],Dr.S.Britto Raj[6]
[1,4]Professor, Department of EEE, RRASE College of Engineering, Chennai, India
[2]Associate Professor, Department of EEE, DHAANISH AHMED College of Engineering, Chennai, India
[3]Professor, Department of ECE, RRASE College of Engineering, Chennai, India
[5]Assistant Professor, Department of ECE, J.N.N Institute of Engineering, Chennai, India
[6]Associate Professor, Department of CSE, RRASE College of Engineering, Chennai, India
[1]dragmephd@gmail.com,[2]virudaianand@gmail.com,[3]kaushikraja2000@gmail.com,[4]atraj77@gmail.com,[5]china_durai1@yahoo.co.in,[6]brittorajs@gmail.com

Abstract

The rapid development of urban improvements over the course of the last decade needs acceptable and practical solutions for smart city transportation, building infrastructure, natural situations, and human pleasure. These issues need to be addressed. Based on various data-mining approaches, this study presents and explores predictive energy consumption models for a smart small-scale steel mill. These models are introduced for the purpose of the study. The Multi-Layer Perceptron (MLP) model has a high level of performance, and its accuracy is 99.44%. Both the MLP and SVM models have good performance, and both have the same precision value of 0.99. The performance of the VP model is quite bad, coming in at 0.76. Both the Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) models have excellent performance, and both have a recall value of 0.99. Both the Multi-Layer Perceptron (MLP) and the Support Vector Machine (SVM) models exhibit good performance, and their F-measure values are both 0.99. The Support Vector Machine (SVM), Fisher's linear discriminant analysis (FLDA), and Quadratic Discriminant Analysis (QDA) models all perform very well and have an identical ROC value of 0.99. The performance of the VP model is subpar, coming in at 74.80%. This system demonstrates that the SVM achieves spark performance when compared to the performance of other classifiers. Additionally, this model is applicable to the creation of energy-efficient structural design, which contributes to the optimization of energy consumption and policy making in smart cities.

Keywords: steel energy, machine learning, FLDA, SVM, QDA

I Introduction

Energy is a precious resource due to population growth. Energy efficiency benefits customers and energy producers. Rapid economic expansion increases global demand for electricity. Electricity is crucial to economic progress and our daily lives [1]. Hence, electricity usage forecasts are vital for a nation or region [2]. Numerous nations are researching energy efficiency and stable electricity delivery. Industry, Transportation, Residential, and Commercial consume energy. Industrial energy use is highest among these four sectors. Industrial energy use must be controlled. The Third Scientific and Technological Revolution simplified life and increased technical innovation and structural change in conventional sectors. Manufacturing is essential to a nation's or region's economy. Several industrialised nations have advanced manufacturing sectors, but they continue to pursue new opportunities and rebuild their manufacturing industries to ensure an unconquerable place in the face of technological innovation and modernization. Germany's "Industry 4.0" uses smart growth to maximise output, material utilisation, and energy use [3].

Since the 1990s, South Korea's manufacturing industry has grown rapidly and driven the economy's rapid expansion. Throughout the 1990s, primary energy demand climbed at 7.5%, faster than financial development at 6.5%. Energy-intensive industries like petrochemicals have advanced rapidly. Industrial

Vol 12 Issue 02 2023
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power usage soared, increasing energy conversion loss and lowering energy intensity. After 2009, energy-industry production increased, but gross energy efficiency decreased [4].Sustainably tailored to environmental needs. Steel is a major emitter. This industry emits 7% of greenhouse gases. The future of steelmaking depends on low-carbon process development and decarbonization. Environmental management is integral to production operations and corporate management worldwide.[5] In wealthy countries, business activities focus on reducing industry pollution. Companies in the European Union aim to meet the European Commission's strict environmental standards by lowering pollutant and greenhouse gas emissions, managing and recycling waste, and reducing raw material consumption. Sustainable development requires all processes to be environmentally sustainable for industry growth.[6] Despite its lengthy history, sustainability was recast at the end of the 1990s and new intensive limits on industry's negative impacts intensified in the first decade of the current century, including dramatic electricity and CO2 emission restrictions. New methods to reduce CO2 emissions and energy sources are needed due to countries' active environmental legislation. Companies in several nations operate under obligatory environmental mechanisms.[7] Many industries, including steel, have adopted sustainability. Industrial energy consumption depends on industrial structure, technology, energy price, economic scale, and national policy. This research proposes using data mining to optimise and manage industrial energy consumption.

It's structured like this. Part 2 reviews the literature, followed by Section 3 on data and description. Section 4 discusses results. Section 6 concludes.

II Literature Survey

Technology helps industries become sustainable. Industry 4.0's strategy is active industrial sustainability [8]. Smart manufacturing systems use new technology, especially digitalization, to boost production. Smart manufacturing may reduce resource use and greenhouse gas emissions. Polish steel industry sustainability was studied due to fuel and energy economy's relevance and industry's need to cut electricity. The Polish steel industry's high energy consumption and CO2 emissions from heat-requiring operations led to its selection as a research focus [9-10].

In the literature, "green steel" emphasises the steel industry's innovativeness in adapting production systems to climate change [11,12]. According to Global Steel Association, the industry has made several innovative changes to reduce its carbon footprint in recent years. Based on Industry 4.0 principles, [13,23]we can describe the following innovations: the increase in the development of new solutions to improve the energy efficiency of steel-using solutions and products in society; the increase in money spent on research and development of an innovative solution to identify new steelmaking technologies that can significantly reduce carbon dioxide emissions; and the improvement

Poland's steel sector ranks second in energy use behind the chemical industry and first in electricity per unit of production sold [14,15]. Poland's short-term steel output projection is fewer than 9 million tonnes [13]. Poland ranks fifth in Europe in crude steel production volume with 5.5% [16,17]. EAF steel mills and rolling mills are most affected by rising energy prices. Steel mills need cheap green energy to compete globally.[18-22]. Energy-saving programmes in the EU will reduce industrial electricity use by 10% due to rising energy prices and supply limits.

III Materials and Methods

In this segment concentrations on the Materials and methods on this research work. The dataset borrowed from UCI data repository.[11] The below table shows that the description of the borrowed dataset.

.No	Features	Data Type	Scale
	Industry Energy Consumption	Numeric	kWh
	CO2	Numeric	ppm
	Lagging Current power factor	Numeric	%

	Leading Current Power factor	Numeric	%
	Number of Seconds from midnight	Numeric	S
	Week status	Numeric	Weekend-0, Weekday=1
	Day of week	Numeric	Sunday=0, Monday=1, Tuesday=2, Wednesday=3, Thursday=4, Friday=5, and Saturday=6
	Lagging Current reactive power	Numeric	kVarh
	Leading Current reactive	Numeric	kVarh
0	Load Type	Numeric	Light Load=0, Medium Load=1, Maximum Load=2

Methodology:

Here this research work focuses on the above specified dataset is using following decision making machine learning algorithms in 10 cross fold validation in one of the leading open source data mining tool namely Weka 3.9.5.

- Multi-Layer Perceptron(MLP)

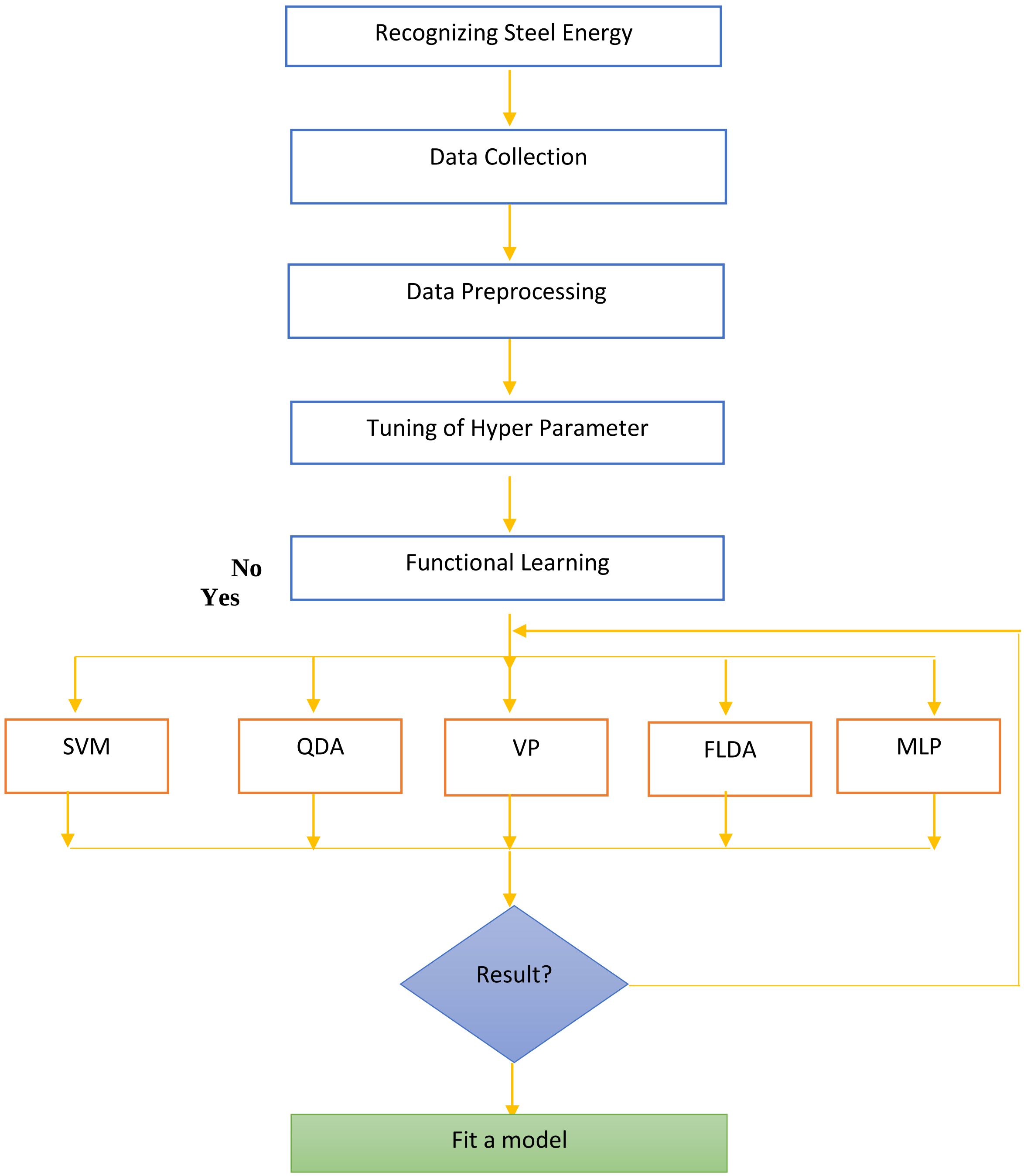

Figure1: Proposed System

- Support Vector Machine(SVM),
- Quadratic Discriminant Analysis(QDA),

- Voted Perceptron(VP),
- Fisher's linear discriminant analysis(FLDA) and

The above diagram shows that the inspiration architecture of the innovative model which is focusing on this research work.

III Results and Discussions

This section focuses on the results and discussions of this research work.The below table 2 shows that the performances of accuracy, precision, recall, F-Measure, ROC and PRC of selected learning algorithms by tuning various parameters.

Table 1: Performance distribution of classifiers

S.No	Classifier	Accuracy	Precision	Recall	F-Measure	ROC	PRC
1	SVM	99.30%	0.99	0.99	0.99	0.99	0.98
2	QDA	96.83%	0.97	0.97	0.97	0.99	0.99
3	VP	75.80%	0.76	0.76	0.74	0.70	0.69
4	FLDA	94.87%	0.96	0.95	0.95	0.99	0.99
5	MLP	99.44%	0.99	0.99	0.99	1.00	1.00

The accuracy level of the SVM classifier is 99.30%, the accuracy level of the QDA is 96.83%, the accuracy level of VP crops is 75.80%, the accuracy level of FLDA is 94.87%, and the accuracy level of MLP yields is 99.44%.

The precision of the SVM classifier is 0.99, the precision of the QDA classifier is 0.97, the precision of the VP classifier is 0.76, the precision of the FLDA classifier is 0.96, and the precision of the MLP classifier is 0.99.

A recall value of 0.99 is achieved by the SVM classifier, whereas a recall value of 0.97 is achieved by QDA, a recall value of 0.76 is achieved by VP crops, a recall value of 0.95 is achieved by FLDA, and a recall value of 0.99 is achieved by MLP.

The F-Measure level produced by the SVM classifier is 0.99, the F-Measure level produced by the QDA classifier is 0.97, the F-Measure level produced by the VP classifier is 0.74, the F-Measure level produced by the FLDA classifier is 0.95, and the F-Measure level produced by the MLP classifier is 0.99.

A ROC value of 0.99 is achieved by the SVM classifier, whereas a ROC value of 0.97 is achieved by QDA, a ROC value of 0.74 is achieved by VP crops, a ROC value of 0.95 is achieved by FLDA, and a ROC value of 0.99 is achieved by MLP.

The PRC value for the SVM classifier is 0.99, while the QDA has a value of 0.97, the FLDA has a value of 0.95, the VP crops have a value of 0.74, and the MLP has a value of 0.99.

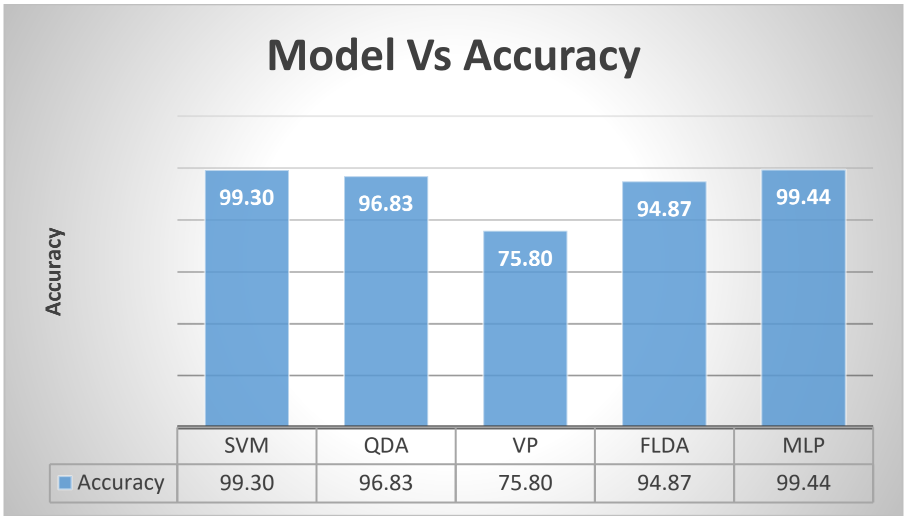

Figure 2: Performance of accuracy values of functional learning

The accuracy performance of several functional learning approaches is depicted above in diagram 2, which can be found here. The MLP model has a high level of performance and an accuracy of 99.44%. The performance of the VP model is only 75.80% effective. The SVM model, the QDA model, and the FLDA model each have corresponding levels of accuracy that are 99.30, 95.83%, and 94.87%.

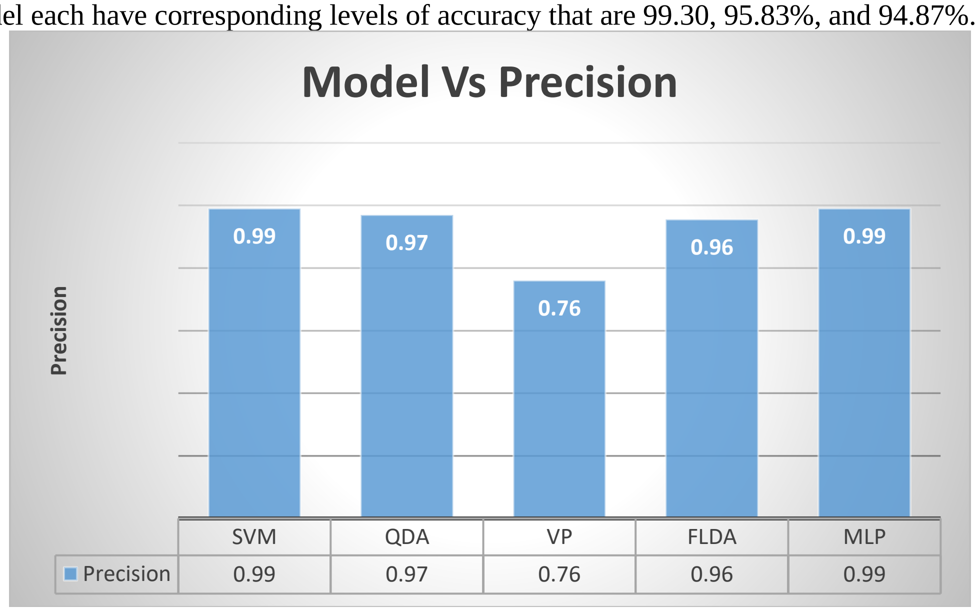

Figure 3: Performance of precisionvalues of functional learning

Diagram 3 depicts the precision performance of several types of functional learning, which can be found up above. Both the MLP and SVM models have high precision scores of 0.99, indicating that they work well. The performance of the VP model is only 0.76, which is not very good. Both the QDA and FLDA models have precision levels of 0.97, with the QDA model having a slight edge at 0.96.

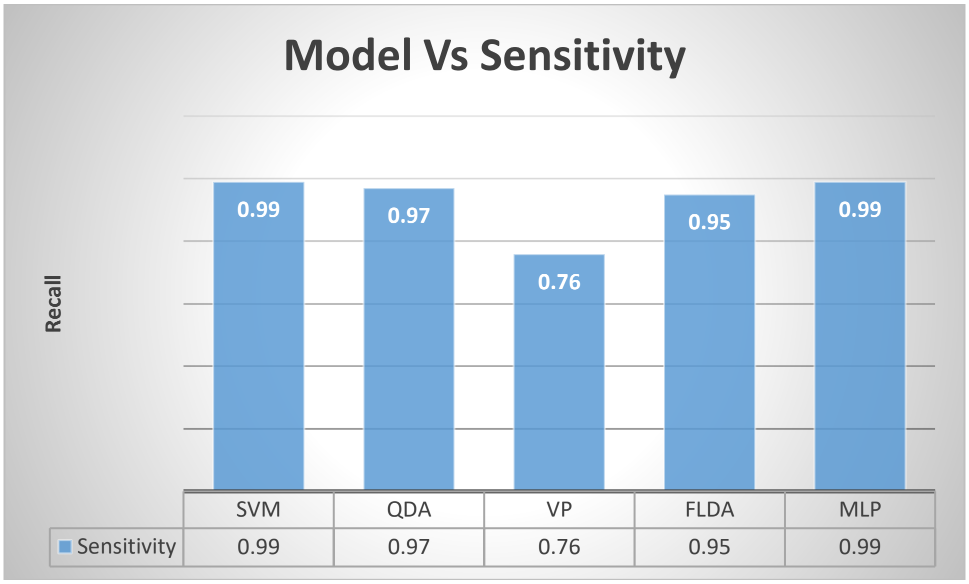

Figure 4: Performance of precision values of functional learning

Diagram 4 depicts the recall performance of several types of functional learning, which may be found above. Recall values of 0.99 are achieved by both the MLP and SVM models, indicating that they are both successful. The performance of the VP model is only 0.76, which is not very good. Both the QDA and FLDA models have recall levels of 0.97, with the QDA model being slightly higher at 0.95.

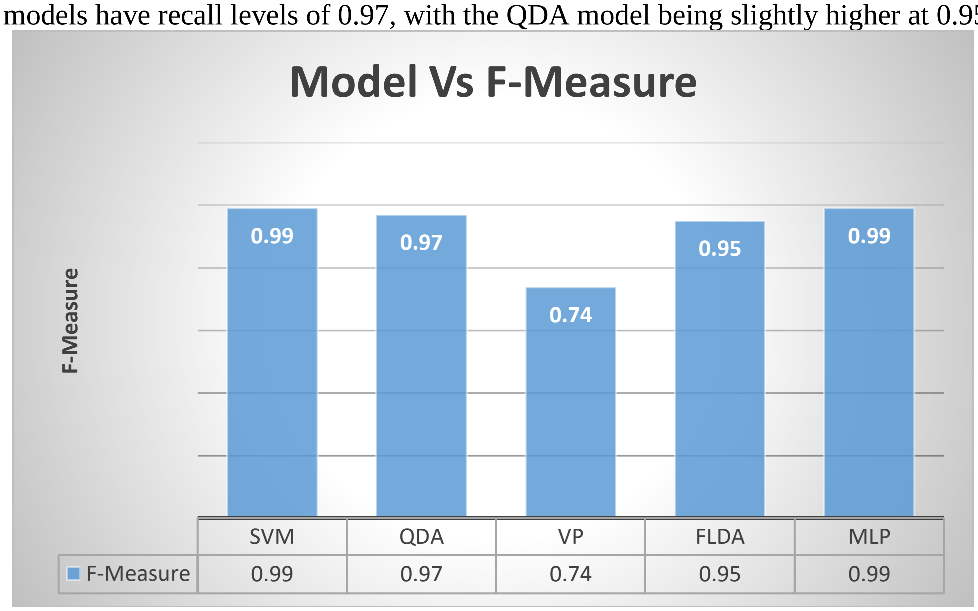

Figure 5: Performance of F-Measure values of functional learning

The performance of various functional learning is illustrated in the diagram 5 that is located further up on this page. The MLP and SVM models both have an F-measure value of 0.99, indicating that they both perform very well. The performance of the VP model is only 0.74, which is not very good. Both the QDA and FLDA models have F-Measure levels of 0.97, with the QDA model being slightly higher than the FLDA model at 0.95.

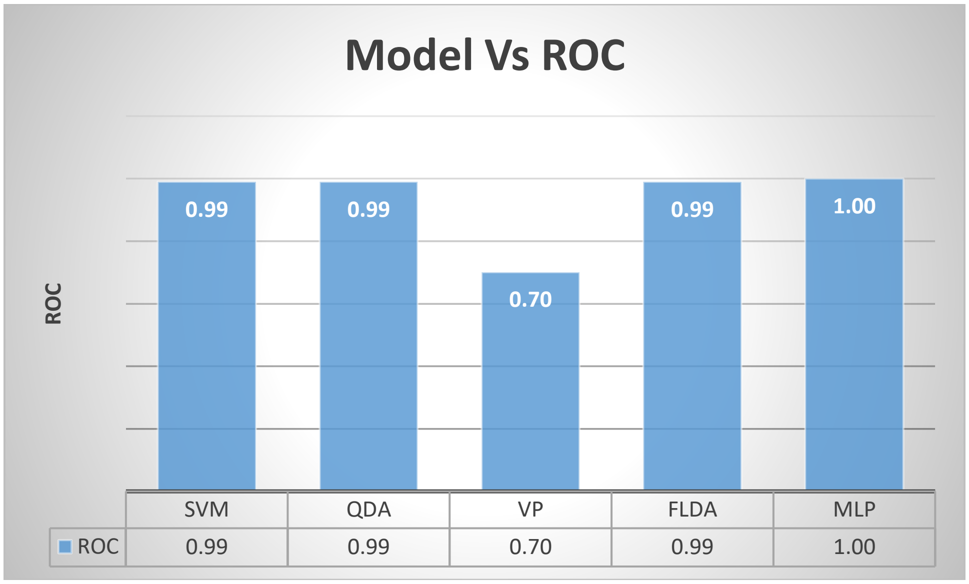

Figure 6: Performance of ROC values of functional learning

Diagram 6 illustrates, for your perusal, how different types of functional learning perform in terms of ROC. All of the models, including MLP, SVM, QDA, and FLDA, perform admirably and have an identical ROC value of 0.99. The performance of the VP model is only 0.70, which is not very good.

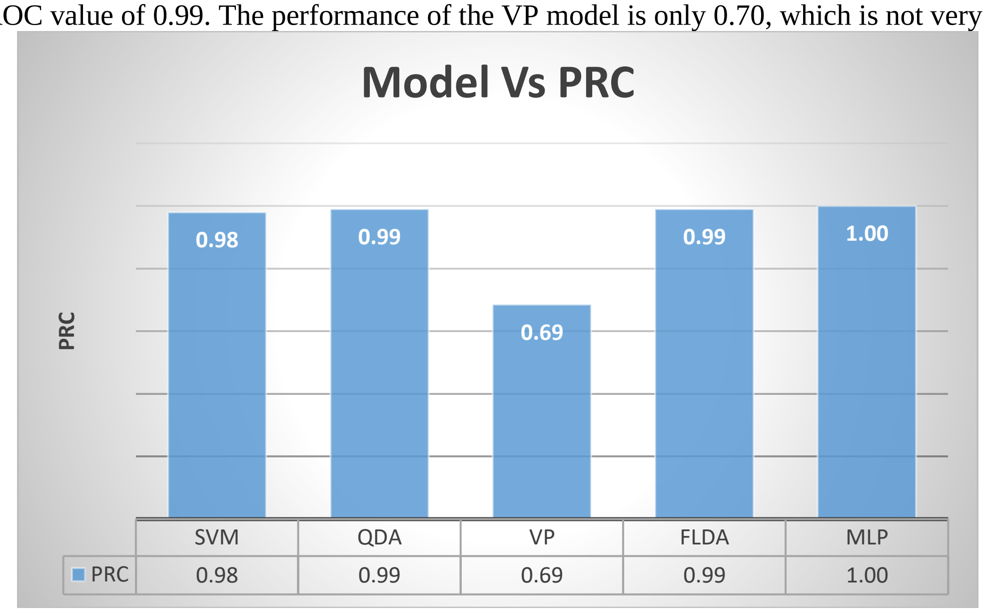

Figure 7: Performance of PRC values of functional learning

The performance of the PRC across its many functional learning areas is illustrated in the diagram located above (number 7). The most advanced level of the PRC for the MLP is level 1. A PRC score of 0.69 indicates that the VP model has low performance. The PRC value for the SVM is 0.98, whereas both the QDA and FLDA models have a PRC value of 0.99.

V Conclusions

According to the findings of this body of research, the MLP model is effective and has an accuracy of 99.44%. Both the MLP and SVM models have good performance, and both have the same precision value of 0.99. The performance of the VP model is quite bad, coming in at 0.76. Both the MLP and SVM models have good performance, and their recall values are both 0.99. The MLP and SVM models perform well, and their F-measure values are both 0.99. The MLP, QDA, and FLDA models also perform well, and their ROC values are all 0.99. The performance of the VP model is subpar, coming in at 74.80%. This system suggested that the Multi-layer perceptron be used in place of the SVM model for identifying steel energy consumption.

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