Predictive Analytics of Productivity Prediction of Garment Employees

Professor: Ceni Babaoglu

Student Name: Maryam Mortezapourdehkordi

Student Number: 501143277

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Ryerson University

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Abstract

As a result of industrial globalization, the garment industry has significantly affected contemporary society. It is a field which employs a vast number of manual procedures and requires much effort. The workers' performance in garment manufacturing enterprises in terms of production and delivery is mainly responsible for meeting the enormous worldwide demand for clothing items. The profit margin of a business rises in accordance with the increase in productivity. When output levels increase, clothing production costs decrease. Therefore, an organization will be able to increase earnings through increased efficiency. Thus, the staff's high level of productivity is of paramount importance. Additionally, some research has been conducted by professionals and academics continuously to determine what factors may impact employee productivity or lead to increased productivity.

On the basis of the data at hand, this study's primary objective is to identify performance-enhancing elements and anticipate how much efficiency will occur. Our dataset includes essential attributes of the garment manufacturing process and the employees' productivity which had been collected manually and validated by industry experts and published in the UC Irvine Machine Learning Repository. We are curious about the following questions:

- which variables are significant and directly have a positive effect?
- How can work efficiency be predicted in a corporation given specific factors?
- Has time affected the efficiency or productivity of employees?

This research aims to discover the answers to the abovementioned questions, and we will apply the classification problem, which determines whether actual productivity reached the target productivity or not. The research will use supervised learning (Regression analysis, SVM, decision trees, k-Nearest Neighbour, Random Forest, …) with Python programming and essential libraries.

Introduction

In many industries, assessing, monitoring, and forecasting employee productivity is crucial since businesses depend on their employees' output and performance. Additionally, several elements, such as incentives given, the industry in which they operate, working hours, day as people frequently think it has a significant impact, the team they work in, and many other features, play an essential role in affecting the productivity of employees. Companies must evaluate and take care of these aspects since they require their employees to be productive.

Based on Marsh, Brush (2002)'s article in the Journal of Industrial Technology, productivity refers to the efficiency and effectiveness with which organizational resources (inputs) are used to create products and services (outputs). Measuring productivity is both a measure of input utilization and assessing whether input utilization increases faster than output. In the case of a garment manufacturing factory, “output” can be taken as the number of products manufactured, whilst “input” is the people, machinery and factory resources required to create those products within a given time frame. The key to cost-effective improvements in output – in “productivity” – is to ensure that the relationship between input and output is properly balanced. For example, there is little to be gained from an increase in output if it comes only as a result of a major increase in input. Indeed, in an ideal situation, “input” should be controlled and minimized whilst “output” is maximized. [1]

Apart from the economic perspective, the garment industry is one of the most labour-intensive industries in the world that requires a large number of human resources to produce its goods and fill up the global demand for garment products. Because of the dependency on human labour, the production of a garment company comprehensively relies on the productivity of the employees who are working in different departments of the company.

A common problem in the industry in this regard is that the actual productivity of garment employees sometimes does not meet the targeted productivity set by the authorities to meet production objectives in time, resulting in enormous losses. Before increasing the productivity of employee performance, it is necessary to know in advance what factors affect and how to predict employee productivity, especially garment employees that are being discussed [2].

According to much research, many key factors affect employees' productivity. Some of these factors include employee training, employee empowerment, and teamwork skills [3]. Other vital factors have been found in research that studied a Bangladesh factory. It has been summarized into nine key elements: working hours, wages and benefits, holidays, discrimination, harassment and abuse, workplace conditions, forced labour, welfare and employment relations [4].

This study aims to solve the problem mentioned by predicting the actual productivity of the employees. To achieve this aim, we applied Machine Learning Algorithms, Deep Neural Network (DNN) models, and Artificial Neural Network (ANN) models on the dataset and compare the results to determine the appropriate algorithm with the best accuracy to predict the actual productivity of the employees.

Literature review

Even though the application of data mining and machine learning techniques are relatively new in the apparel industry, they have quickly gained popularity in related research. A considerable amount of work is done in improving various operations in the apparel production supply chain, with the help of data mining, which is discussed in the following section. For instance, achieving a good garment fit has been a big issue in the apparel industry [5]. Nonetheless, attempts have been made to address the issue using various data mining techniques. There are a few sub-areas of research within this that are highly focused, including finding the most relevant body measurements to develop a new sizing system [6,7] and evaluating the fit of the garment using virtual try-on [8]. Zakaria et al. employed principal component analysis, k-means clustering, and regression tree to address issues related to the identification of the most important body measurements [9]. Similarly, Hsu and Wang [10] used Kaiser's eigenvalue criteria along with the Classification and Regression Trees (CART) decision tree algorithm to identify and classify significant patterns in the body data. On the other hand, forecasting is another popular research area where data mining has been used for sales forecasting [11,12] and demand forecasting. An application of time series on e-commerce to forecast sales trends has been discussed in the study by S.V. Kumar et al. [13,14].

With their proposed method, it is possible to achieve both short-term and long-term forecasting. The study by Z. Al-halah et al. [15] used fashion images to predict the popularity of styles in the future. They trained a forecasting model using these style images to represent the trend over time. Yet another application Symmetry 2020, 12, 984 3 of 20 of data mining extensively worked upon is recommender systems [16,17].

An excellent overview of the existing apparel recommendation systems is presented in [18]. It highlights the improvement required in creating a comprehensive apparel and user profile to improve the existing recommendation systems and shows the need for long-term recommendations in design and manufacturing. On these lines, Z.H.U. Ming et al. [19] considered both user preference and behavioural data to design an online recommendation system aiming to provide increased relevance to the recommendations. In the study [20], C. Skiada et al. generated association rules using real Point-of-Sales (POS) data to provide recommendations and to understand the customer's needs and behaviour while shopping online or offline.

Furthermore, significant attention has been paid to utilizing image recognition and pattern recognition [21,22], and deep learning for the classification of fashion images [23,24]. W. Surakarin et al. focused on classifying upper-body garments using a Support Vector Machine (SVM) with a linear kernel to train the machine-learning model to classify clothing into sub-categories and realized an overall accuracy of 73.57% [25]. On the other hand, C.-I. Cheng et al. [26] used neural networks and fuzzy sets for garment characterization and measurements. More recently, generative adversarial networks were used by K.E.A. et al. [27] to translate target attributes into fashion images. This method has the advantage of working when the number of attributes to be manipulated in an image is large, which is usually the case with the data in the fashion and apparel industry [28]. This technique is still at a nascent stage, however, and holds immense potential to advance the task of the automatic generation of fashion styles. Classification techniques have also been used to categorize fabric and sewing defects in the industry using computer vision for different applications (e.g., see [29,30] for fabric defects and [31] for garment defects).

It is interesting to note that classification systems have also been employed in image retrieval systems. For example, A. Vuruskan et al. [32] created an intelligent system to select fashion for non-standard female bodies using a genetic algorithm and neural network. More recently, the convolutional neural network has become popular for the task of classification of clothing images. H. Tuinhof et al. [33] trained a convolutional neural network to classify images of fashion products and proposed a system that takes one image as input from the user and provides a range of similar recommendations.

Luca Donati et al. [34] worked on the automatic recognition and classification of various features of the garment, solely by rendering images of the products, and achieved an accuracy of 75%. In some other works, Bossard et al. [35] focused on identifying the clothes worn by people in images by first locating the upper body in the image and then extracting the features for garment classification using a Support Vector Machine and Random Forest with an accuracy of 35.03% and 38.29%, respectively. An interesting finding of this study was the different training accuracies between 38% and 71% for different garment categories.

The study in [36] proposed a cross-model search tool, which can do both image annotation and image search by training a neural network with fashion attributes. When it comes to the classification of garments, most of the studies are associated with image recognition and computer vision. However, when a customer searches for a garment on an online retail channel, they often use certain keywords (garment attributes, categories, styles) while using a retailer's website, or use 'hashtags' while searching on social media retail channels, such as Instagram.

Classifying garments using text instead of images can be useful in this scenario. An efficient classification framework for categorizing garment categories according to their attributes can be useful for customers—as it provides a better user experience when they receive the correct product suggestions—as well as businesses, as it directly influences sales. In this context, in a study by Hammar, K. et al. [37], they train a classifier using data from Instagram of clothing attributes and used it to predict the clothing with an f1 score of 0.60. The study in [38] trained a support vector machine by using the text representing product description to classify fashion styles by brand and achieved an accuracy of 56.25%. As has been realized by examining the extant literature in the field of data mining and machine learning in the apparel industry, most of the research related to the classification of an apparel product Symmetry 2020, 12, 984 4 of 20 has been focused on using visual features, while the research using attributes as ‘words’ to train the classification model is scant. Consequently, this study uses ‘words’ to build a classification framework that can predict the category and sub-category of garments, given their product attributes.

Using a trained neural network to predict the production cycle time, the overall error of 6 groups is within 5%, and that of 3 groups is between 5% and 10%. Therefore, this neural network can be used to predict the future production cycle time and predict the overall production time of clothing [39]

Machine learning algorithms such as decision tree, Naïve Bayes, Random Forest and SVM were applied by study Bhatia, Arora, and Tomar 2016 [40] for the presence of diabetic retinopathy, and the results proved that the model could help in detecting symptoms earlier. Outperformed results were found in a study conducted by Kruppa et al. 2013 [41] for credit risk prediction using the framework of machine learning algorithms such as random forests (RF), k-nearest neighbours (KNN) and bagged K nearest neighbours (BKN). Furthermore, a study by Balla, Rahayu, and Purnama 2021 [42] proved a promising result in predicting employee productivity which is one of the most substantial factors in any organization. The study applied three classification algorithms, namely, Neural Network (NN), Random Forest (RF) and Regression Linear (RL). Random forest showed minimal values of the correlation coefficient, MAE, and RMSE, which reflect that RF is very appropriate in predicting employee productivity.

Decision tree classification algorithms utilized by Attygalle and Abhayawardana 2021 [43] for investigating and visualizing employee productivity and any other social phenomenon with evidence. Moreover, decision tree methods and data mining tools were employed by Ďurica, Frnda, and Svabova 2019 [44] to build a model for predicting the financial difficulties of Polish companies. The results presented a prediction power of around 98% and more. In addition, Mahoto et al. 2021 [45] used three machine learning algorithms (Multiclass Random Forest, Multiclass Logistic Regression, and Multiclass one-vs-all) in order to help business workers to set product pricing and discounts depending on customer behaviour; the model showed outstanding results in product price prediction.

On the other hand, a prediction model has been built by study Sorostinean, Gellert, and Pirvu 2021 [46] using decision tree methods and data mining tools to investigate the effect of decision tree methods and ensemble learning for improving performance prediction in assembly assistance system. The results demonstrated that the gradient-boosted decision trees were the best through all the decision-tree-based methods. Some studies evaluated workers' performance in textile companies by using ML and ensemble learning algorithms, such as the study Saad 2020. [47] which applied different Machine learning algorithms, including, decision trees and bagging algorithms to achieve the highest accuracy. The CHAID model produced high-level specificity and sensitivity.

Four different ML algorithms, including, support vector machine, optimized support vector machine (using a genetic algorithm), random forest, XGBoost and Deep Learning, were used by El Hassani, El Mazgualdi, and Masrour 2019 [48] for predicting the overall equipment effectiveness (OEE) which is a performance measurement of the manufacturing industry. Deep learning and random forest with cross-validation manifest the best results for predicting OEE.

Additionally, an approach built-in study De Lucia, Pazienza, and Bartlett 2020 [49] of ML and logistic regression used for financial performance prediction by focusing on predicting the accuracy of main financial indicators such as Return of Equity (ROE) and Return of Assets (ROA). The ML algorithms were performed perfectly for predicting ROE and ROA. All studies and research work mentioned above focused on combining two or more classifiers and how this integration of different techniques and algorithms can help in prediction.

Covering the largest number of people with the fewest number of sizes is the optimal scenario in the context of tailoring. Therefore, through the use of objective interestingness measures-based feature selection and feature extraction, Viktor et al [50]. have discovered the relevant subsets of body measurements.

Likewise, Hsu et al. [51] have applied comprehensive factor analysis and a decision tree-based data mining approach to develop an innovative sizing system for male workers in Taiwan to facilitate the manufacturing process. Usually, people seek products of high quality but at low cost, and thu,s manufacturing the products without any defect turned into a challenge to the manufacturers so as to fulfill the demand of the customers.

Lee et al.[52] present a hybrid Online Analytical Processing (OLAP)-association rule mining-based intelligent quality management system so that manufacturers are able to explore the garment defect patterns in a timely manner to improve the quality. To achieve better quality assurance in the garment industry, Hsu et al. [53] have developed a slippery genetic algorithm-based process mining system (sGAPMS) to optimize the fuzzy association rule. Rahim et al. [54] have proposed a methodology for mining the industrial-engineered manufacturing data of the garment industry. Based on the two-stage cluster approach, namely, Ward's minimum variance method and K-means algorithm, Hsu et al. [55] have developed a data mining framework to extract valuable patterns and improve industrial standards so as to enhance production.

Like the aforementioned study [56], Lee et al. have focused on quality assurance in the garment industry, and the eminent authors of this paper deployed a radio frequency identification (RFID) based recursive process mining system.

Ruba Obiedat and Sara Toubasi released a study that focused on predicting garment employee productivity using different machine learning algorithms such as J48, RF, SVM, NB, and RBF with and without ensemble learning algorithms, including, bagging and Adaboost. Their proposed approach succeeds in enhancing almost all classifiers' performance. J48 was superior compared with all other applied algorithms. The best results were obtained by J48 combined with Adaboost on 20th iterations with 0.9916 accuracy, 0.0083 MAE and 0.0908 RSME. Consequently, J48 with the Adaboost algorithm was found to be the best for garment employee productivity prediction. [57]

Goal

My goal is to build models to classify and predict the productivity of garment employees for my dataset. Meanwhile, I would like to compare performance, Deep Neural Network, Regression Models (Linear, Lasso, Ridge, Poisson, decision tree, KNN regression, SVR, Random Forest) and boosting algorithms (xgboost, Gradient boosting) Along with the Artificial Neural Network Model (RBFNN, GRNN, …) set.

Machin Learning metric

Evaluation Metrics

To evaluate our model performance and measure the errors, we have considered three evaluation metrics named Mean Squared Error, Mean Absolute Error, and Mean Absolute Percentage Error. All the metrics have been chosen by considering their benefits and interpretation. Details about the metrics are discussed below.

Mean Squared Error (MSE)

MSE basically measures the average squared error of our predictions. For each point, it calculates the square difference between the predictions and the target and then averages those values. The higher this value, the worse the model is. MSE can be formulated as:

$$\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \quad (8^*)$$

Mean Absolute Error (MAE)

MAE is calculated as an average of absolute differences between the target values and the predictions. The MAE is a linear score which means that all the individual differences are weighted equally in the average. What is important about this metric is that it penalizes huge errors that are not as that badly as MSE does. Thus, it is not as sensitive to outliers as mean square error. MAE can be formulated as:

$$\frac{1}{N}\sum_{i=1}^{N}|y_i-\hat{y}_i| \quad (9^*)$$

Mean Absolute Percentage Error (MAPE)

MAPE is basically expressed as the relative error preference. For each instance, the absolute error is divided by the target value, giving a relative error. The primary advantage of using MAPE is the clear interpretability of its results. MAPE provides a single value of percentage for the error. Therefore, when the average range of the prediction is known, it can be simply estimated what the predictions are going to look like. MAPE can be formulated as:

$$\frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (10*)$$

Accuracy and Precision

We use the following formulae to evaluate, accuracy and precision. The Mathews correlation coefficient (MCC) is a machine learning measure which is used to check the balance of the binary (two class) classifiers. It considers all the true and false values, which is why it is generally regarded as a balanced measure that can be used even if there are different classes.

$$\begin{aligned}
\text{accuracy} &= \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FN}+\mathrm{FP}+\mathrm{TN}} y \\
\text{precision} &= \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \\
\text{recall} &= \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \\
F_\beta &= \frac{(1+\beta^2)\times\text{recall}\times\text{precision}}{\text{recall}+\beta^2\times\text{precision}} \\
F_1 &= \frac{2\times\text{recall}\times\text{precision}}{\text{recall}+\text{precision}}.
\end{aligned}$$

Dataset

In this study, the dataset used is garments worker productivity, which is a public dataset because it is taken from the UCI repository website. The dataset used in this study was published in 2020 with 15 attributes and has 1197 instances. All attributes' details are shown in the below tables.

A brief descriptive statistics of the selected dataset

Each attribute for the training dataset is described in the following two tables. The first table, which includes a description of each attribute, was taken from the original UCI Repository. The second table, which shows which characteristics are numerical and whether they are continuous or discrete, and which features are categorical and whether they are nominal or ordinal, is obtained by looking at each attribute individually. It also offers some preliminary findings regarding the ranges and typical values of the attributes.

Table 1: Attribute description

ID	Attribute	Description
1	Date	Date in MM-DD-YYYY
2	Quarter	A portion of the month. A month was divided into four quarters
3	Department	Associated department with the instance
4	Day	Day of the Week
5	Team	Associated team number with the instance
6	Targeted_productivity	Targeted productivity set by the Authority for each team for each day.
7	Smv	The Standard Minute Value, is the allocated time for a task
8	Wip	Work in progress. Includes the number of unfinished items for products
9	Over_time	Represents the amount of overtime by each team in minutes
10	Incentive	Represents the amount of financial incentive (in BDT) that enables or motivates a particular course of action
11	Idle_time	The amount of time when the production was interrupted due to several reasons
12	Idle_men	The number of workers who were idle due to production interruption
13	No_of_style_change	Number of changes in the style of a particular product
14	No_of_workers	Number of workers in each team
15	Actual_productivity	The actual % of productivity that was delivered by the workers. It ranges from 0-1

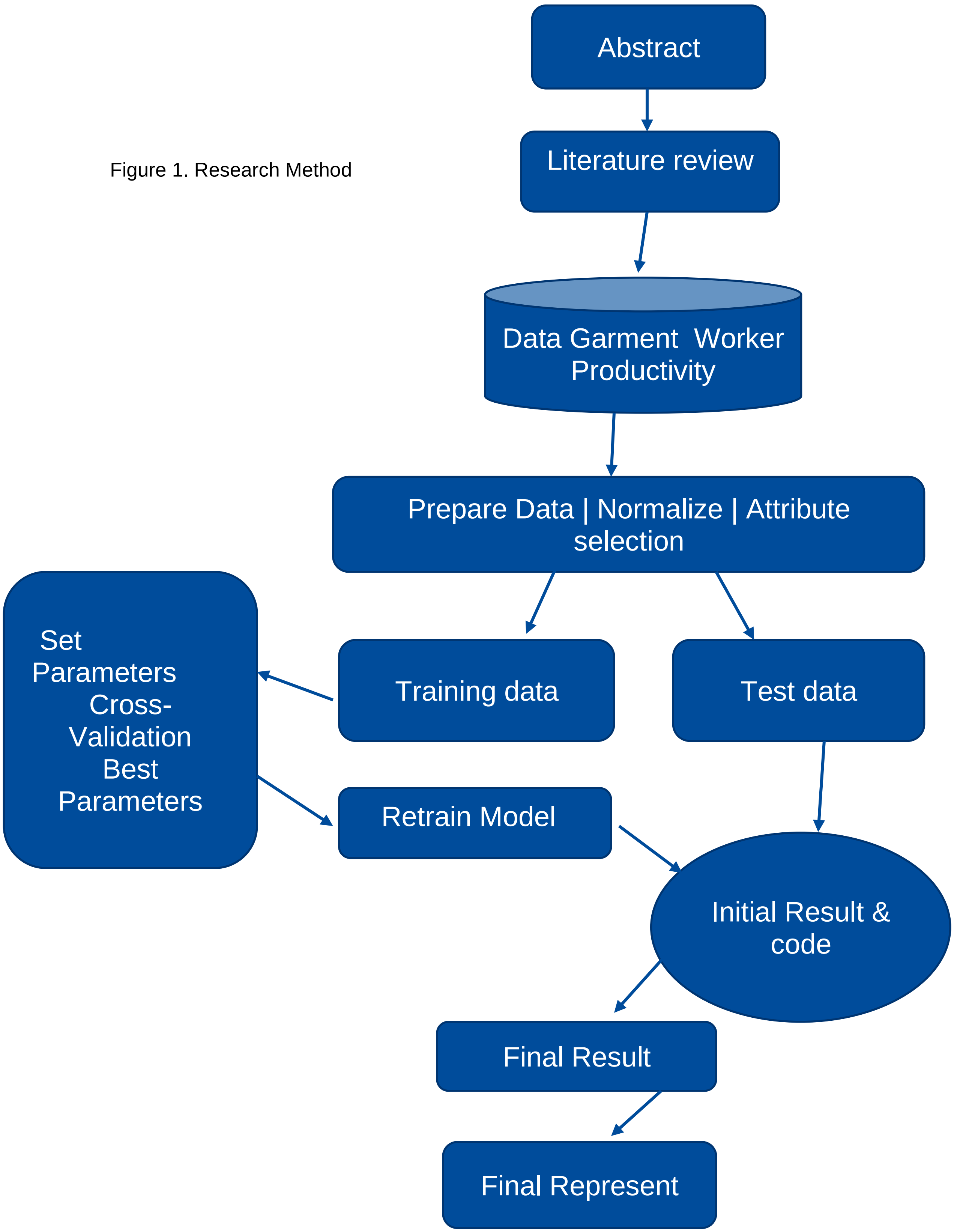
Table 2: Attribute type

ID	Attribute	Type	Sub-type	Comments
1	date	Categorical	Ordinal	Contains duplicates. Range from 2015-01-01 to 2015-03-11, which is 59 days. Can drop
2	quarter	Categorical	Ordinal	Has 5 values. Quarter 1-5
3	department	Categorical	Nominal	Has 2 values. 'sewing' and 'finishing'
4	day	Categorical	Ordinal	Has 6 values. Friday does not appear. Day off?
5	team	Categorical	Nominal	Has 12 values, for 12 teams
6	targeted_productivity	Numerical	Continuous	Has 9 unique values - range is 0.07 - 0.8. Very likely to have outliers
7	smv	Numerical	Continuous	Values range from 2.9 to 54.56
8	wip	Numerical	Discrete	Values range from 7 to 23122. Mistake? Extreme outliers
9	over_time	Numerical	Discrete	Values range from 0 to 25920. Extreme outliers. The majority are 0, 960, 1440
10	incentive	Numerical	Continuous	Values range from 0 to 3600. Extreme outliers. The majority is 0

ID	Attribute	Type	Sub-type	Comments
11	idle_time	Numerical	Continuous	Values range from 0 to 300. Extreme outliers. The majority is 0
12	idle_men	Numerical	Discrete	Values range from 0 to 45. The majority is 0
13	no_of_style_change	Numerical	Discrete	Only has 3 values - 0,1,2. The majority is 0
14	no_of_workers	Numerical	Discrete	Ranges from 2 to 89. The majority is 8. There are some numbers that include decimals i.e. 51.5. Mistake?
15	actual_productivity	Numerical	Continuous	Values range from 0.2337 to 1.1204

Graph methodology

Figure 1. Research Method



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Appendix

A link to a repository on GitHub:

https://github.com/Maryam-Dehkordi

The link below refers to the source of this data:

https://archive.ics.uci.edu/ml/machine-learning-databases/00597/garments_worker_productivity.csv