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Performance Improvement in Manufacturing Shop Floor Operations of Developing Countries Based on Three Characteristics of Information Flow

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Abstract

The management of information flow for production improvement has always been a target in the research. In this paper, the focus is on the analysis model of the characteristics of information flow in shop floor operations based on the influence that dimension (support or medium), direction and the quality information flow have on the value of information flow using machine learning classification algorithms. The obtained results of classification algorithms used to analyze the value of information flow are Decision Trees (DT) and Random Forest (RF) with a score of 0.99% and the mean absolute error of 0.005. The results also show that the management of information flow using DT or RF shows that, the dimension of information such as digital information has the greatest value of information flow in shop floor operations when the shop floor is totally digitalized. Direction of information flow does not have any great influence on shop floor operations processes when the operations processes are digitalized or done by operators as machines.

Keywords

Developing Countries, Information Flow Characteristics, Machine Learning, Shop Floor Operations, Value of Information Flow

1. Introduction

Quality and timely product delivery have always facilitated the improvement of

performances in Small and Medium Size Enterprises (SMEs) in the performance improvement long term strategy. Performance amelioration has always been at the center of scientific research and many researchers demonstrated that performance improvement is a function of information sharing and decision making. The management of information flow (MIF) moves towards digitalize information known as information of things and it is a key for performance improvement [1] [2], but in some developing countries the concept of internet of things applied to the MIF is still not yet a mere event due to the lack of technology transfer and the random economic situation [1] [2] [3]. It is then an opportunity to work over a progressive transition from the traditional MIF in shop floor operations to the digital MIF. A proper MIF renders manufacturing companies continuously efficient when stochastics and none stochastics event related to machines and operators' behaviors occur [3] [4] [5]. This paper focus on shop floor of manufacturing companies in developing countries which are moving towards a digitalize MIF but which still have some lacks that result in poor decision making when facing operations productions and later cause a decrease of performance of the company. A good MIF is also based on the analysis of information flow characteristics, according to Mbakop *et al.* [6] and presented by **Figure 1** and **Figure 2**, the MIF consists of giving to information flow a value in order to facilitate decision-making in shop floor operations for performance improvement of companies [6]. Decision-making in company is also subject to

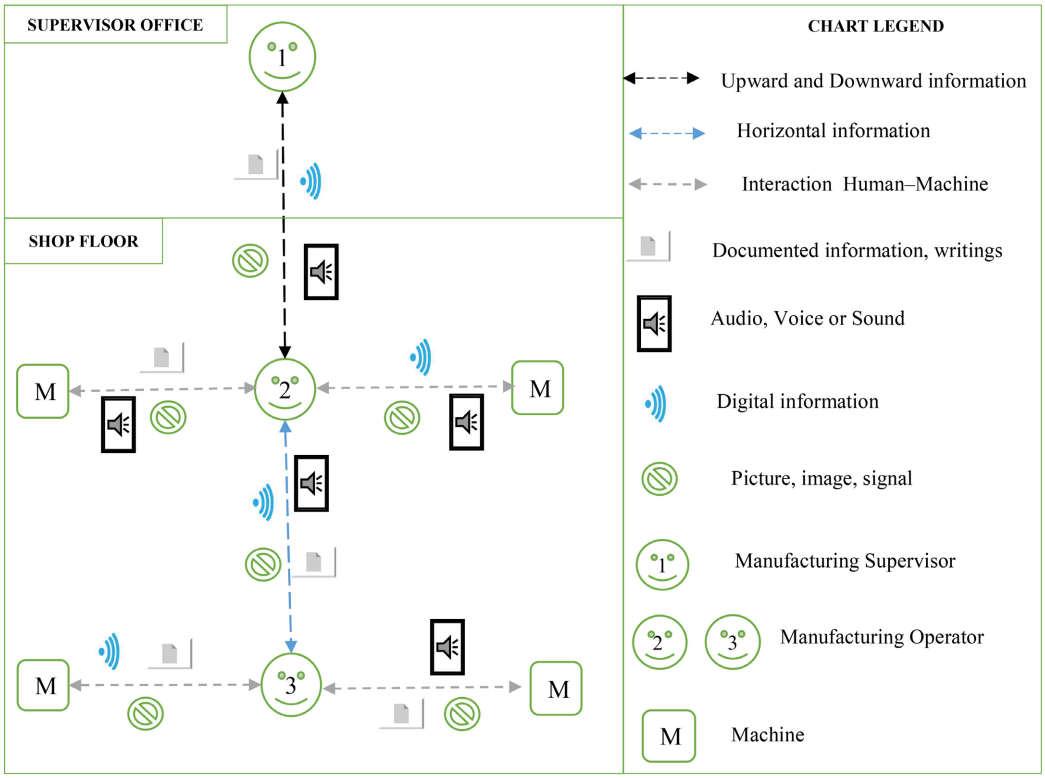


Figure 1. Information flow sharing in small-and medium-sized manufacturing companies of developing countries.

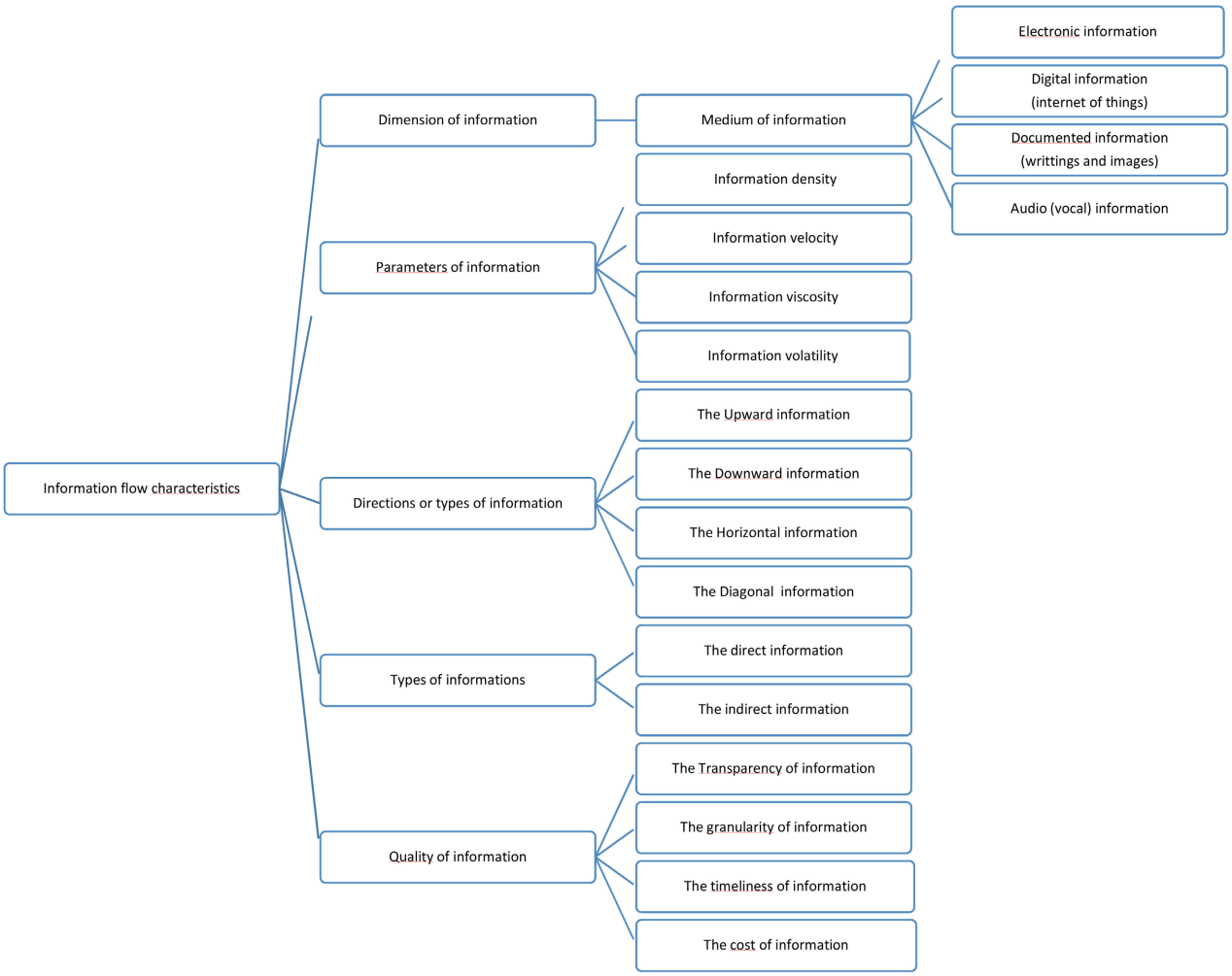


Figure 2. General characterization of information flow.

the information flow received, information flow coming from the tactic level to the strategic level doesn't have the same weight or consideration as the information coming from the strategic level to the tactic level when the company isn't totally digitalize, likewise information coming from the operational level to the tactic level and the tactic level to the operational level, the impact on information flow on decision-making by shop floor operators (machines, computers, humans) is visible and has to be considered, so a none-timely information won't enable the good performance of the production chain. An information flow in the production chain can then be attributed a value which will have an influence on productions operations. Thus, the integration of information flow in shop floor operations processes. From what the literature research presented, till now research works were done in the determination of the value of information flow (VIF) by integrating one of the characteristics of information flow (CIF) namely quality, later dimension because the companies were almost digitalized, but they haven't considered that they are some companies trying to move from the traditional MIF to the digitalization MIF and also in their works they haven't inte-

grate the influence of at list two CIF in their analysis of the VIF to facilitate decision making in manufacturing companies. Some tried to determine the VIF with the quality of information flow by using methods of technical audit, process information integration and recently, dimension of information by using the Value-Added Heat Map (VAHM) method which leads to the degree of digitalization of processes in shop floor, but never dimension and quality at the same time. It is therefore important to consider in this paper a new model that will include information quality, direction, and direction on the value of information flow to analyze the integration of information flow in shop floor operations processes and later using the machine learning algorithms.

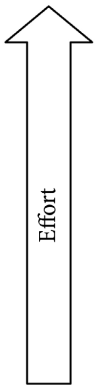
This paper aims at integrate the CIF in the determination of the VIF to facilitate decision making by operators in the shop floor process using the approach of machine learning, by taken in consideration the hypothesis, that some of the CIF can be scale according to Tomanek and Schroder [7]. The accomplishment of this gold lead us to related works on the determination of the VIF and Machine Learning Classification Algorithms Techniques, then a proposal methodology for the analysis of the VIF and a comparative analysis of the Machine Learning Classification Algorithms namely: Decision Trees, Gradient Boosting, KNN, Support Vectors Classifiers, Logistic Regression, Random Forest, and Gaussian Networks Bayesian on the obtained result.

2. Related Work on the Determination of the Value of Information

In industrial and job processes, materials and information flow are always on motion except that their motions can be described by contrary direction. An information can then stop the flow of materials in process, cause the materials not to be in process, from this, it is important to have a look on the value of information that are in the process or that may trigger the process. According to the literature, there are many ways to define or to consider the value of information: in the job operations sequences, the value of information can be linked with the benefit that and information adds to a process or service, [8] [9] [10]. The value of information flow can be considered as a measure for the avoidance or minimization of the bullwhip effect [11]. Considering the integration of information flow in a process be it shop floor or not, the value of information is based on the quality of information that is characterized by accessibility, transparency, timeliness and granularity [12] [13]. The value of information can be created by information, which is transmitted correctly. Complete and in a timely manner [14] [15], by avoiding disturbances and media disruptions. Considering the works of Tomanek and Schröder 2016 [7], the value of information flow is function of scale of the dimension of information flow as presented in **Table 1**. Considering the presence of materials on a production line in shop floor, the value of information can be deducted from the impact that materials undergo on shop floor, and also the value of information flow can be determined by knowing the

Table 1. Value added heat map-evaluation scale for information flow [7].

Categorization	Value Added Level	Dimension of Information Flow	Scale
No Added Value	0	Insufficient, incorrect or unnecessary exchange of information	
Limited Added Value	1	Written exchange of information (e.g. paper document, fax, e-mail, etc.)	
	2	Verbal or visual exchange of information	
	3	Electronical exchange of information not real-time (e.g. by spreadsheet application)	
	4	Electronical exchange of information real-time (e.g. by system-application)	
Maximum Added Value	5	Digital exchange of information real-time (e.g. by Internet of Things and Services)	



digitalization degree in a context of industry 4.0 using the method of Value-Added Heat Map (VAHM) [6].

Many methods were used to determine the value of information.

2.1. Process Integration Method

According to the process integration method, Aubert *et al.* [16] integrated the quality of information flow in the and their results show that, the more the information quality cost is low, the more of information is high and more the information process integration is high also according to Equation (1):

$$PI = \frac{VA - \sum_{j=1}^{n} C\left(a_j\right) + C\left(tr_j\right) + C\left(ti_j\right) + C\left(g_j\right)}{VA} \tag{1}$$

where VA: Value added by the process,

a_j : accessibility for activity *j*,

ti: timeliness for activity *j*,

$C\left(x_j\right)$: cost of providing property *x* for activity *j*,

tr: transparency for activity *j*,

gi: granularity for activity *j*,

$$QI = \sum_{j=1}^{n} C\left(a_j\right) + C\left(tr_j\right) + C\left(ti_j\right) + C\left(g_j\right) \tag{2}$$

QI: value of the quality of information flow.

Berente and Vandenbosch [17], proposed another form of computation of the value of the process integration depending of the quality of information, instead of considering the cost of information quality, they have tried to attribute to

every quality of information the factor of time. They carried out an audit and they determine the different time referring to information quality characteristics. The obtained formula of the process integration value is given by Equation (3) and the value of information that can be considered from it is given by Equation (4).

$$PI_t = 1 - \frac{\sum_{j=1}^{n} T(a_j) + T(tr_j) + T(ti_j) + T(g_j)}{TT} \tag{3}$$

where TT: total time taken by the process,

a_j : accessibility for activity j

ti: timeliness for activity j

$T(x_j)$: time of providing property x for activity j

tr: transparency for activity j

gi: granularity for activity j.

$$QI = \frac{\sum_{j=1}^{n} C(a_j) + C(tr_j) + C(ti_j) + C(g_j)}{TT} \tag{4}$$

QI: value of the quality of information flow.

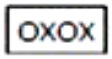
The works of Aubert *et al.* [16], Berente and Vandenbosch [17], were focused on the quality of information flow to influence the value of information in the process integration.

They have justified it by the fact that, it is not easy neither to quantify the cost and the time related to accessibility, timeliness, transparency and granularity. To quantify the time of the accessibility of an information is a difficult task and doing that takes much more time. That is why, it is very important to look for another way round to compute the value of information flow.

2.2. Value-Added Heat Map (VAHM) Method

According to the Value-Added Heat Map proposed by Tomanek and Schroder [18], which is an innovative visualization tool that indicates the level value creation concerning production relevant factors. The VAHM enables to have a view on the added value level of production relevant factors by using colors scaling and it by developing key performance indicators it finds also its application in determine relevant factors like the internal circulation of information flow. To analyze the VIF, they have done an audit in the company in with they have mapped the flow of information and the results of the audit lead them to scale the information that were given a more added value to the process. Table 1 and Table 2 illustrate the information flow in circulation in the shop floor and the VAHM respectively. Though the Value-Added Heat Map analyses the information flow, it shows a possibility on how deficient information or defective information can be cause to the losses of time. In their work they have only considered that the medium of information with is the dimension of information can be scale. They haven't integrated the scaling of direction of information flow, of the parameters, of the types and of the quality of information flow.

Table 2. Value Stream Analysis—symbols for the visualization of an information flow [7].

Symbols for the information flow	Meaning
	Manual information flow
	Electronic information flow
	Electronic information flow
	Levelled production planning
	Route of a kanban card

2.3. Digitalization Degree Method

The value of information was then the estimate function of the digitalization degree, the layout-specific digitalization degree indicates, which percentage the degree of information flow promotes added value. It is computed from the ration of the sum of each information transfer multiplied with the corresponding value-added level and the amount of transferred information per time unit multiplied with the highest possible value-added level according to Equation (5) developed by [17].

$$\text{Digitalization degree} = \frac{\sum_{i=1}^{N}\left(\text{Information Transfert} \times \text{Value Added Level}\right)_i}{N \times \max\left(\text{Value Added Level}\right)} \times 100 \quad (5)$$

Information Transfer $i = 1, \cdots, N$;

N = Amount of transferred information per time unit;

Value Added Level = 0, … 5.

2.4. Information Quality Value Stream Mapping (IQVSM)

Busert and Fray (2020) [19], based on value stream mapping (VSM), the authors used this method to visualize the information flow that will serve for production planning and control to improve the performance of the shop floor. They considered the following sub-characteristics of information quality: Granularity, timelines (frequency), and accessibility of information to improve the value that an information flow may have on the shop floor. To reach their goal, they carried out interviews from which they received information concerning the shop floor to build up scenarios for their analysis. To harmonize the information quality, they computed the tolerance of the quality of information; the lower the tolerance, the higher the value of information. They noticed that the percentage tolerance of information quality is very important in planning control and the shop floor management.

2.5. Deep Learning Method Based on Artificial Neural Network

Mbakop *et al.* (2021) [20], used deep learning method base on the characteristics of information flow. In their analysis of the value of information flow, the authors took all the characteristics of information flow to find the value of information using artificial neural network behaving as a deep learning model. The obtained value of information flow was in the unit interval and their results showed that parameters should not be included in information flow to have a good management. For it is difficult to assume or determine the value of the quality of information in the unit interval but you can at least know if the quality of information is accurate or not.

Therefore, this paper does not consider that the characteristics of information flow are data defined in the unit interval, but rather consider that that they are binary data and to analyze them classification algorithm of machine learning will be used to observe the influence that information characteristics such as quality, direction and dimension have on the value of information flow in a shop floor operation. The considerations of all these characteristics of the information will give a real knowledge on information flow management in the context of developing countries because it is not all the SMEs manufacturing company which are high industrialized. It is important to consider that a digital information (dimension) of information can face disruption according to the network of the environment such digital information will cause losses and will no more have "5" has added value. It is therefore important to bring out a new method or a new model to determine or to analyze the value of information flow defined as the integration of information flow in shop floor of developing countries for the decision-making. This paper will present two modeling approaches, the process integration modified approach and the machine learning approach.

3. Machine Learning Algorithms

The analysis of the integration of information flow (IIF) based of the value of information flow (VIF) in shop floor of developing using a machine learning algorithm approach has not yet been a study focus according to article that was read in the literature. This is justified, because the development of information characteristics has been updated by [6]. Machine Learning Methods have been used in many applications in industries. Machine learning techniques and their different roles. Researchers have characterized machine learning in trees groups, namely: Supervised Learning, Unsupervised Learning, Reinforcement Learning. This paper is concerned with supervised learning as noted in **Figure 3**.

Support Vectors (SVC) is an algorithm of ML technique use for classification and prediction analysis due to it high accuracy which is based on statistical analysis, it has been developed for pattern recognition, classification, it uses a great number of data [18] [21] [22] [23], it objective relies on is the individualization of hyperplanes parallel to error minimization.

Decision Tree (DT) is an algorithm of ML with is also used for classification

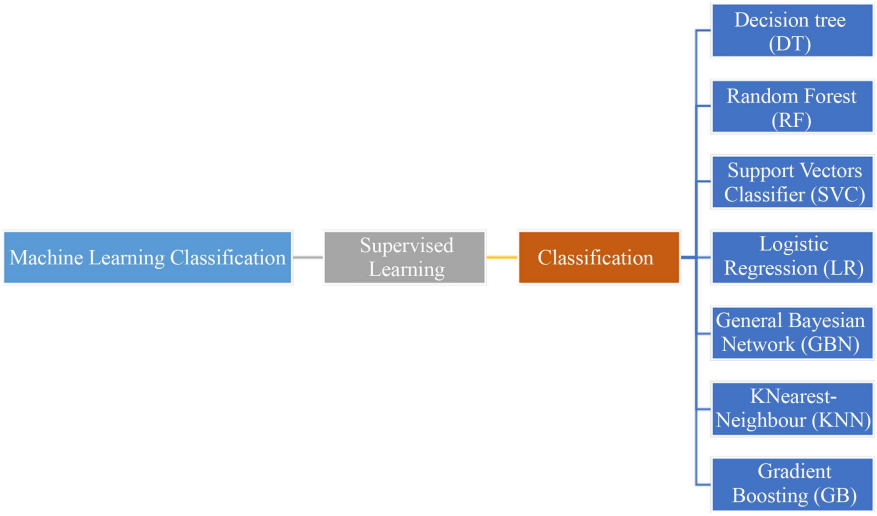


Figure 3. Classification of algorithms of supervised learning.

and prediction analysis. The main purpose is to expose the structural information contained in data, his network is formed of nodes which represents features (inputs) and the leaf nodes which represent the output [24] [25].

Logistic Regression (LR) is a classification function that uses class for building and uses a single multinomial logistic regression model with a single estimator, it is also used for prediction and it is usually states where boundary is between 0 and 1 [26] [27].

Bayesian Networks (BN) is a statistical classifier that predict the class of probability, Bayesian networks are graphical models, showing the relationship between the subset of attributes and BN have exhibited high accuracy and speed when applied to large databases [26] [27] [28] [29].

Random Forest (RF) is a classification algorithm contains of a set of trees, in which similar independent vector vectors are distributed, and every tree issues a voting unit for the most common category in input [30] [31] [32].

KNearest-Neighbour (K-NN) is an algorithm mostly used for classification problems and pattern recognition, this method classifies cases based on the relationship between variables and can be used for both classification and regression [33] [34].

Gradient Boosting (GB): is a machine learning algorithm formed of weak learners as DT to build up a strong learner, it has a peculiarity cost function optimization [35] [36].

4. Proposed Methodology

In this paper the methodology is based on two main approaches. The proposed methodology is presented by **Figure 4**. The first approach is based on the new proposed integration of the information model in shop floor processes, which passes through the mathematical modelling of the information flow based on information characteristics related to the production process. The second approach

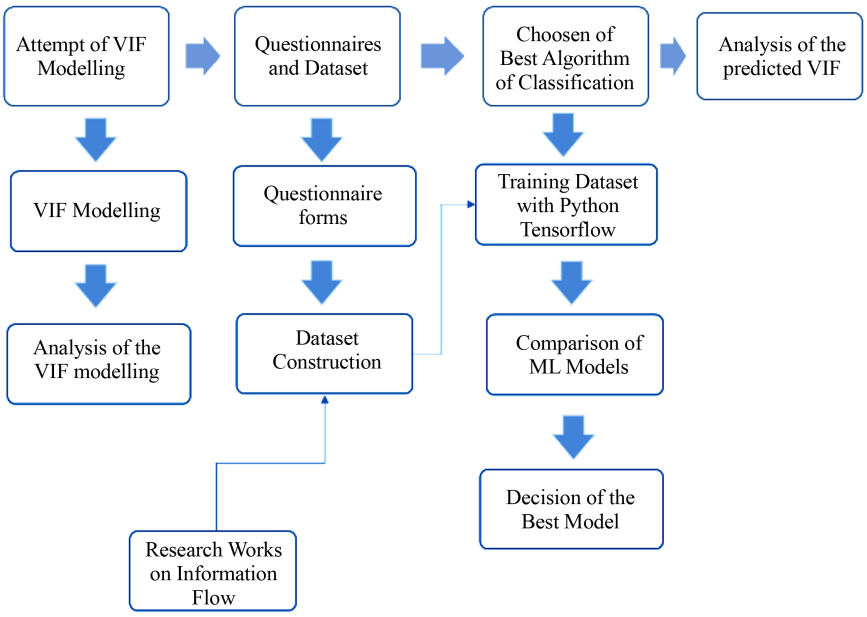


Figure 4. Method of determination or prediction of the VIF with supervised machine learning algorithms.

is based on the usage of the constructed questionnaires form to analyze the value of information using machine learning algorithms. To build this questionnaire form, some considerations of previous research works on information flow has been taken into account. Then, the software python Tensorflow will be used to split and train the dataset, to compare the different model of ML by given each accuracy of ML model then chose the one that has the best accuracy and lastly interpret some predicted VIF.

For the dataset acquisition a survey was carried out, that survey was based on the submission of online answer sheet question to employee concerning, the importance of each characteristics of information flow on the value of information flow and that will be later be exploited to have the correlation matrix of the information flow. For the sample questionnaire kindly have a look in appendix. A simple mathematical modelling of the VIF will be developed depending on the results of survey and the various characteristics of information flow. The comparative analysis of VIF will be a way of chosen the suitable model analysis for paper.

4.1. Modeling of the Value of Information Flow in Shop Floor Operations

The IF is a row matrix M_{IF} of 5 rows Matrix ($X_k, 1 \le k \le 3$) representing all the 3 components of the IFC and all the IFC are not dependent each other. Each of X_k row matrix has a x_i component that is totally binary for one case and for an order one only the dimension information value will not be binary data but they will derive from the scale of information dimension as presented in **Table 2**.

For each $X_k = (x_i)$,

$$x_i = \begin{cases} \text{Dimension}, 1 \le i \le 6 \\ \text{Direction}, 1 \le i \le 4 \\ \text{Quality}, 1 \le i \le 4 \end{cases} \quad (6)$$

Dimension of information has as component,

$$X_1 = (x_{11}, x_{12}, x_{13}, x_{14}, x_{15}, x_{16}) \quad (7)$$

Direction of information flow has as component,

$$X_2 = (x_{21}, x_{22}, x_{23}, x_{24}) \quad (8)$$

For quality, there wasn't a consideration of the fifth sub characteristics which is the cost of information flow in this paper, that is why quality contain 4 components.

Quality of information flow has as component,

$$X_3 = (x_{31}, x_{32}, x_{33}, x_{34}) \quad (9)$$

An information flow shared in a shop floor or organization for services or product manufacturing or delivery has the following Matrix given by Equation (10).

$$M_{IF} = (X_1, X_2, X_3) \quad (10)$$

From the definition of the characteristics of information flow that constitute an information flow (IF), this paper doesn't include the type and the parameters on the IF. Taking in consideration the weight attributed to the sub-characteristics of information flow in the audit, W is defined as the weight attributed to each of the following sub-characteristics.

Dimension value of information can be modeled as:

$$DI = \frac{W(x_{1j})}{W_{1m}} \le 1 \quad (11)$$

$W(x_{1j})$: the weight of the dimension of information;

W_{1m}: the maximum weight of the dimension of information.

Direction value of information can be modeled as:

$$DRI = \frac{W(x_{2j})}{W_{2m}} \le 1 \quad (12).$$

$W(x_{2j})$: the weight of the direction of information;

W_{2m}: the maximum weight of the direction of information.

Quality value of information can be model as:

$$QI = \frac{\sum_{j=1}^{4} W(x_{3j})}{W_{3Tm}} \le 1 \quad (13).$$

$W(x_{3j})$: the weight of the quality of information;

W_{3Tm}: the maximum weight of the quality of information.

The VIF for every information flow arriving in the system is described by Equation (14), is presented by **Figure 5**.

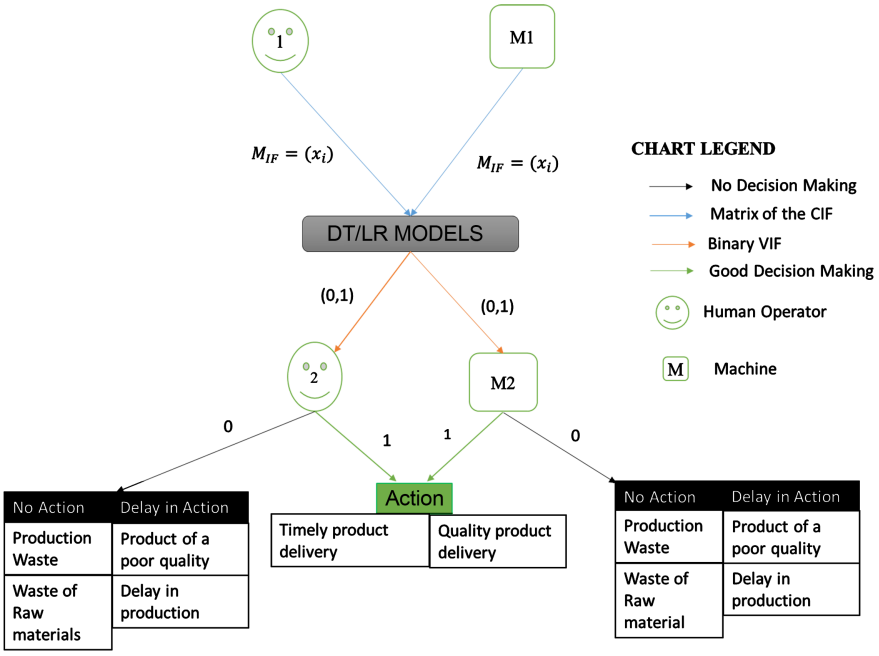


Figure 5. Illustration of the analysis of VIF with the GB model for decision making.

$$VIF = DI + DRI + QI \leq 3 \quad (14).$$

It is therefore necessary to examine the characteristics of information flow which minimize or maximize the value of information flow in shop floor operations.

It will be for a heavy task to examine the characteristics of information flow which maximize or minimize the value of information flow. For this reason, machine learning algorithms methods seem to be a proper method to analyze this model and give us the characteristics that maximize or minimize the value of information flow by taking in consideration the information from the audit.

4.2. Questionnaire and Dataset Collection

Questionnaires were built and submitted to industries of some developing countries and the objective of the questionnaire is to have a general view on the influence of information flow characteristics on decision making and performance which is illustrate by the value of information flow. Questions sample were like: Tick the sub-characteristics of the dimension of information flow which can have influence on the value of information flow, from your above response answer if there is a good or a bad value of information flow. The obtained dataset couldn't be analyzed by the VAHM, but because that are voluminous but it can be used to build up a new model of the integration of information flow in shop floor operation and also to choose a machine learning method. From these questionnaires two dataset 1 and 2, will be generated, the first one will consider the responses of the questionnaires and the second one with considered the dataset 1 and the scale value of dimension of information flow proposed by [7].

4.3. Comparative Analysis of Machine Learning Algorithms: Supervised Learning

The comparative analysis will be based on the score and metrics of the classification algorithms models given by Equations (16)-(18), The error criteria such as mean square error (MSE) and the root means square error (RMSE), and Mean Absolute Error (MAE) are the performance criteria of machine learning models. with y' the predicted and y the actual VIF, N is the number of samples.

$$\mathrm{MSE} = \sum_{i=1}^{N} \frac{\left(y_i' - y_i\right)^2}{N} \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{N} \frac{\left(y_i' - y_i\right)^2}{N}} \tag{17}$$

$$\mathrm{MAE} = \sum_{i=1}^{N} \left| \frac{y_i' - y_i}{N} \right| \tag{18}$$

4.4. Heat Map of Information Flow Describe by the Correlation Matrix When Having Binary Data

When the CIF are totally binary or except the dimension which isn't binary, from the data collected in a sharing of an information flow based of its characteristics in shop floor of developing countries, it happens that the correlation matrix is the same and its shows the relationship or the dependency between the CIF as presented by Figure 6.

The correlation Matrix for the two cases indicates the following observations.

Observation 1: A perfect dependency (1.0) of every characteristics of information flow with each other, which mean technically that, the information flow sharing depends on the CIF.

Observation 2: A negative dependency (−0.2) indicates between each of the sub characteristic of the dimension of information flow a light independency between each of the sub characteristics, when digital is present, each of the other dimension has to be absent, it confirms the assumption made in hypothesis 2.

Observation 3: A negative dependency (−0.3) between each of the sub characteristic of the direction of information flow, which signify to avoid confusion in decision making by operators in shop floor an information flow may not come from two level of decision making, but even if it is the case the influence of dependency is less than 0.5, so it will not have a lot of effect on the value of information flow as long as data are binary.

Observation 4: From observations 1, 2, and 3, the influence of levels of decision making is more than the one of the dimensions of information flow looking at the absolute value of dependency coefficient. From all the above observations, it doesn't exist a total dependency between the features or information flow characteristics, therefore this dataset can't be used for regression algorithms but only for classification algorithms as long as machine learning is concerned. The focus will be on which model is more proper for the analysis of the value of

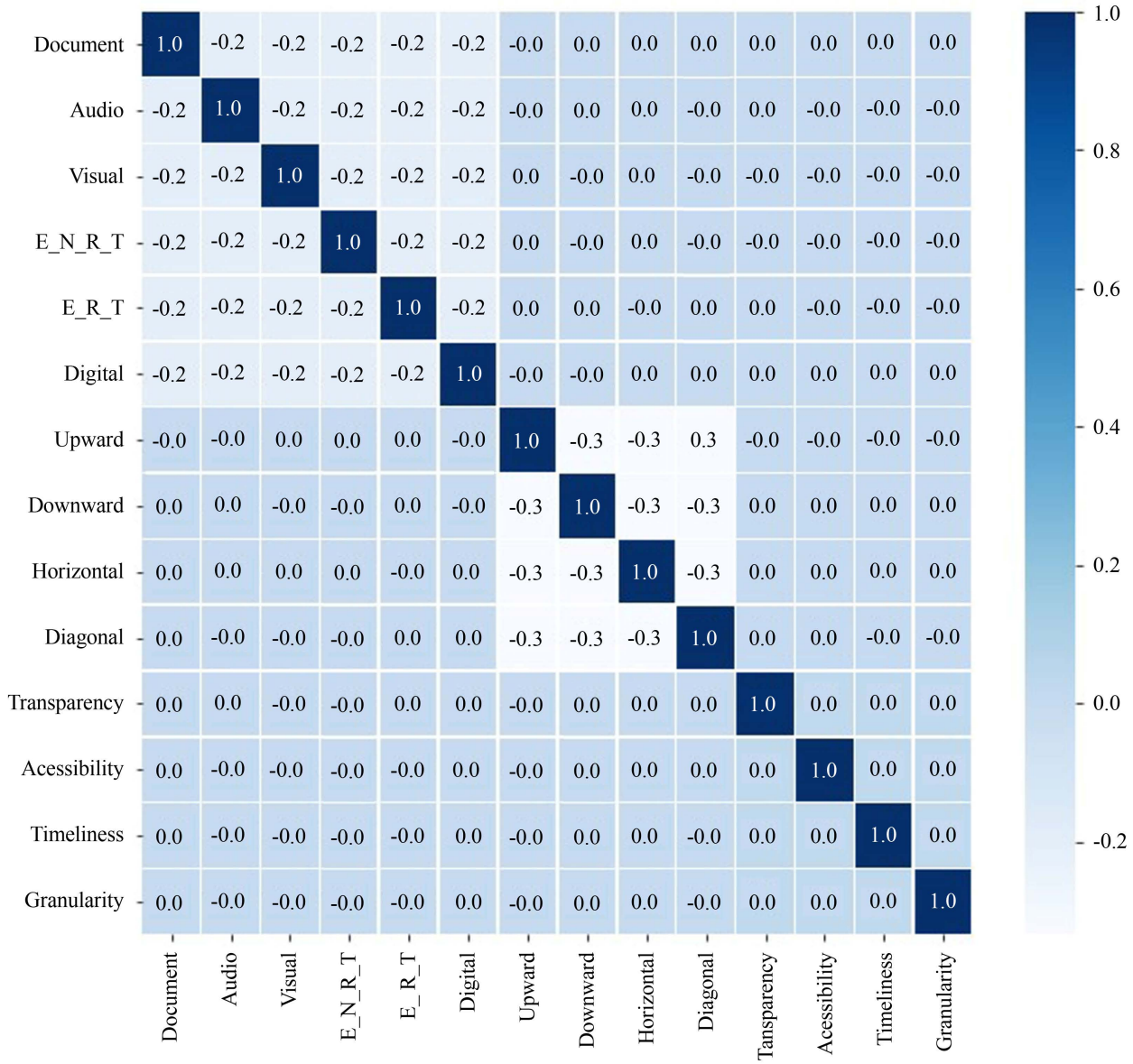


Figure 6. Correlation matrix of the CIF.

information flow and also which model will help us to determine the characteristics of the information flow which maximize the value of information flow.

5. Results and Discussion

5.1. Comparison of Machine Learning Models: Classification Algorithms

In this paper, the focus is based on these various classification algorithms: DT, KNN, RF, SVC, LR, GNB, GB. After splitting and train the dataset, the results obtained from our computation with python enable us to be focus on performance metrics. The splitter percentage of dataset 1 and 2 was as follow: 80 percent for the training and 20 percent for the prediction.

The training scores of the classification ML models are presented in Figure 7 and Figure 8 for dataset 1 and 2 respectively. From Figure 7 and Figure 8, all the ML models have been well trained, but DT has an excellent learning ability in the dependencies that exist between the VIF and the characteristics of information flow, when data are mixed. GBN is the only model which has a least coefficient, because the data obtained aren't completely random but it derives from an audit. To choose the best model, the accuracy of each model will be an important aspect.

From Figure 8, GB, KNN, SVC, LR, DT, RF, and GB are suitable models with a score of 0.99 for the determination of the VIF.

According to Figure 7 and Figure 8, the predicted models are all accurate for the analysis of the information flow. But from the performance model evaluations of algorithms metrics loss function for both dataset 1 and 2 are given by Figure 9 and Figure 10 respectively, the best algorithms are the Decision Trees

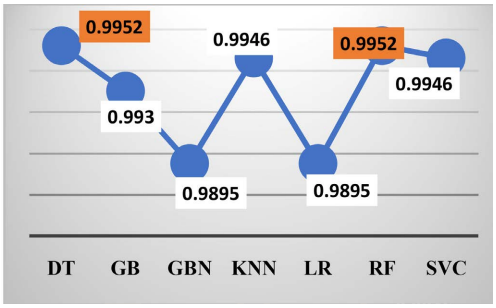


Figure 7. Scores evaluation for dataset 1.

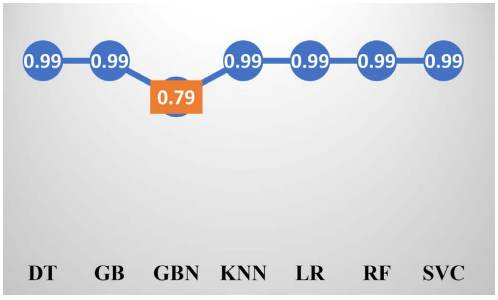


Figure 8. Score evaluation for dataset 2.

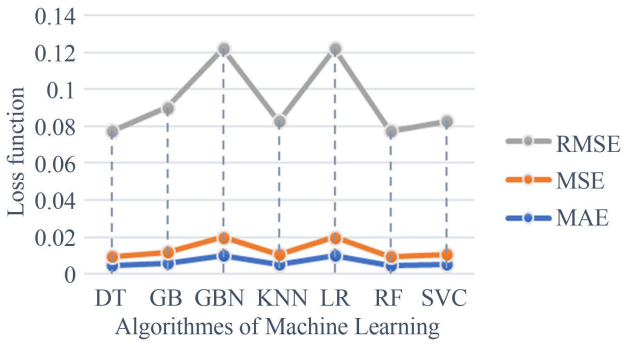


Figure 9. Loss function metrics of the dataset 1.

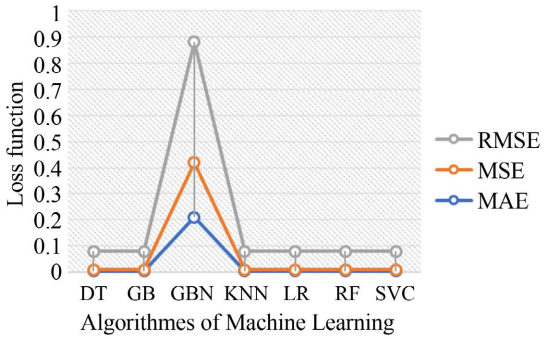


Figure 10. Loss function metrics of the dataset 2.

Model (DT) and Random forest (RF) for case 1 with a score of 0.9952, the MAE = 0.0047 and the RMSE = 0.068.

From **Figure 9** and **Figure 10**, it comes that the suitable models for the analysis of VIF in this paper are the decision trees (DT) and the Random Forest (RF), because of their excellent score and loss function. In a situation where information flow characteristics is binary data and when dimension are scale as in model of industry 4.0, DT/RF will help the managers of the shop floor operations to select what information characteristics give a good VIF to enable decision making.

5.2. Interpretation of the Prediction Analysis

An information flow sharing between shop floor operators (humans and or machines) during a operations processes can have a VIF that is to considered or not according to the characteristics of the information flow. Depending on the kind of operators some, information characteristics differs it can be illustrated by this example: an information flow can be complex for man operator but not for an automated machine, a paper information is more for a human operator than for machine or computer, digital information is more suitable for interconnected machine than for humans, so whether an information flow is destined for a machine, human or computer each characteristics of information flow will correspond to each operator for a better interpretation for a better decision making, that is why **Figure 3** presents DT/RF model in decision-making.

5.3. Analysis Based on the Dimension and the Direction under Good Quality of Information Flow Dataset 1 and 2

With the DT/RF models on dimension of information flow it comes that:

DT/RF 1: An information flow shouldn't derive from more than one medium, if not the value of information flow will be 0. Concerning the document, the Audio, Visual, Electronic non-real time (E_N_R_T) information and the electronic real time information (E_R_T), the CIF can give out a good VIF if the information flow has to be transparence (1) and well details or granular (1), the information flow must not come from than one direction. In shop floor where is are still paper information, or audio, transparency of information, accessibility, granularity, timeliness has to be maximized.

DT/RF 2: Concerning digital information, the model gives out a good value of information flow when there aren't the disruptions that can occurs in the information sharing from the directions, and also from the network problems in the developing countries, this then can't allow machines to operate in their optimum performance level.

DT/RF: In this work the model shows us that, here the direction of information does not have a mere influence of the value of information flow except when the information is coming from more than one decision making level.

It is not in all developing countries that directions of information have the same effect of information as in this work (where it represents a total independence decision making production operators with facilitate it performance for production). This is because of the presence of human personnel at the decision level of operations, the order from the tactical level or a supervisor may have indirectly a great influence on the human operator, consequently on his production action.

The results obtained from this paper based on the dimension and the direction of information flow are comparable with the one of [20]. In the sense that, digital information flow can provide a good value of information flow when there is no disruptions in the transmission process of information. And also the shop floor may have a good performance when the dimension of information flow and the direction have data which are all equal to 1. Though the works of [20] was focused on mixed data (binary and non-binary) the results obtained from this analysis show that a shop floor can become more efficient if information flow in the shop floor are well managed.

6. Conclusions

Information management in shop floor operations can also be focused on the analysis of integration of information flow which plays a great role in decision making and performance operations improvement, a well-organized MIF based on the CIF will increase the efficiency of the SMEs. This article aimed at modelling the integration of information flow in shop floor operations based on the value of information flow and also analyze this integration of information flow with machine learning (KNN, SVC, LR, DT, GBN, RF, GB) algorithms. The novelty in this paper, is the integration of the dimension and the direction of information flow in the analysis of the integration of information flow in shop floor operations known as the value of information. The analysis aspect of the models using the audit technique and machine learning algorithms present DT/RF algorithms as the best models that maximize the VIF function.

Which is to say that, dimension of information flow has to be of a good medium as digital for information flow to be well integrated in process operation and also a paper information can give out a good value of information flow in shop floor operations if it is transparent and granular for both dataset 1 and 2 respectively. In production process an information flow shouldn't come from

many directions or from many levels of decision for it can cause disruptions in information flow analysis then reduces the value of information flow can consequently the performance of the shop floor. The present work is limited when the information flow arrives randomly for production processes, so it will be for a great scientific help to evaluate the performance of the shop floor based on the arrival of random information.

Conflicts of Interest

The authors hereby declare that there are no potential conflicts of interest in terms of authorship, research and/or publication of this article.

References

[1] Kim, H.J. (2017) Information Technology and Firm Performance: The Role of Supply Chain Integration. *Operations Management Research*, **10**, 1-9. https://doi.org/10.1007/s12063-021-00184-1

[2] Hall, D.C. and Johnson-Hall, T.D. (2021) The Value of Downstream Traceability in Food Safety Management Systems: An Empirical Examination of Product Recalls. *Operations Management Research*, **14**, 61-77. https://doi.org/10.1007/s12063-021-00184-1

[3] Agu, O.C. and Mbah, S.A. (2013) African Firms Manufacturing and Economic Development: Is Africa Effectively Competing in Manufacturing in the World Market. *IOSR Journal of Humanities and Social Science*, **12**, 34-46.

[4] Saymeh, A.A.F. and Sabha, S.A. (2014) Assessment of Small Enterprise Financing, Case of Jordan. *Global Journal of Management and Business Research*, **14**, 6-17.

[5] UNIDO (United Nations Industrial Development Organization) (2021) Challenges to Industry 4.0. UNIDO Knowledge Hub. https://hub.unido.org/training-modules-industry-4

[6] Contador, J.C., Satyro, W.C., Contador, J.L and Spinola, M.M. (2020) Flexibility in the Brazilian Industry 4.0: Challenges and Opportunities. *Global Journal of Flexible Systems Management*, **21**, 15-31. https://doi.org/10.1007/s40171-020-00240-y

[7] Evans, S. and Bahrami, H. (2020) Super-Flexibility in Practice: Insights from a Crisis. *Global Journal of Flexible Systems Management*, **21**, 207-214. https://doi.org/10.1007/s40171-020-00246-6

[8] Ojstersek, R., Acko, B. and Buchmeister, B (2020) Simulation Study of a Flexible Manufacturing System Regarding Sustainability. *International Journal of Simulation Modelling*, **19**, 65-76. https://doi.org/10.2507/IJSIMM19-1-502

[9] Mbakop, A.M., Voufo, J., Biyeme, F., Ngozag, L.A. and Meva'a, L. (2021) Analysis of Information Flow Characteristics in Shop Floor: State-of-the-Art and Future Research Directions for Developing Countries. *Global Journal of Flexible Systems Management*, **22**, 43-53. https://doi.org/10.1007/s40171-020-00257-3

[10] Tomanek, D.P., Hufnagl, C. and Schröder, J. (2020) Determining the Digitalization Degree of Information Flow in the Context of Industry 4.0 Using the Value Added Heat Map. In Kolinski, A., Dujak, D. and Golinska Dawson, P., Eds., *Integration of Information Flow for Greening Supply Chain Management*, Springer, Cham, 159-179. https://doi.org/10.1007/978-3-030-24355-5_10

[11] Tomanek, D.P., Schröder, J. and Wirz, M. (2016) Value Added Heat Map—A New Method for the Optimization of Production Space. 13*th International Conference*

on Industrial Logistics (*ICIL* 2016), Zakopane, 28 September-1 October 2016, 315-323.

[12] Porter, M.E. and Millar, V.E. (1985) How Information Gives You Competitive Advantage. *Harvard Business Review*, **63**, 149-16. https://palfreymanventures.net/porter-and-millar-1985.pdf

[13] Durugbo, C., Tiwari, A. and Alcock, J.R. (2010) Managing Information Flows for Product-Service Systems Delivery. *Proceedings of the* 2*nd CIRP IPS*2 *conference*, Linköping, 14-15 April 2010, 365-370.

[14] Durugbo, C., Tiwari, A. and Alcock, J.R. (2013) Modelling Information Flow for Organisations: A Review of Approaches and Future Challenges. *International Journal of Information Management*, **33**, 597-610. https://doi.org/10.1016/j.ijinfomgt.2013.01.009

[15] Lee, H., Padmanabhan, V. and Whang, S (1997) The Bullwhip Effect in Supply Chains. *Sloan Management Review*, **38**, 93-102.

[16] Berente, N. and Vandenbosch, B. (2004) Factors Inhibiting Information Process Integration, Case Western Reserve University, USA. *Sprouts*: *Working Papers on Information Systems*, **4**. https://espace.library.uq.edu.au/view/UQ:276655/Burton-Jones_JAIS-TDW08-129.pdf

[17] Berente, N. and Vandenbosch, B. (2009) Information Flows and Business Process Integration. *Business Process Management Journal*, **15**, 119-141. https://doi.org/10.1108/14637150910931505

[18] Reese, J. (2016) Management von Wertschöpfungsketten. Unternehmenskooperation ohne Märkte. Verlag Franz Vahlen, München, 80. https://doi.org/10.15358/9783800651979

[19] Busert, T. and Fay, A. (2020) Information Quality Focused Value Stream Mapping for the Coordination and Control of Production Processes. *International Journal of Production Research*, **59**, 4559-4578. https://doi.org/10.1080/00207543.2020.1766720

[20] Mbakop, A.M., Biyeme, F., Voufo, J. and Meva'a, J.R.L. (2021) Predictive Analysis of the Value of Information Flow on the Shop Floor of Developing Countries Using Artificial Neural Network Based Deep Learning. *Heliyon*, **7**, Article ID: E08315. https://doi.org/10.1016/j.heliyon.2021.e08315

[21] Wang, N., Liang, H., Zhong, W., Xue, Y. and Xiao, J. (2012) Resource Structuring or Capability Building? An Empirical Study of the Business Value of Information Technology. *Journal of Management Information Systems*, **29**, 325-367. https://doi.org/10.2753/MIS0742-1222290211

[22] Aubert, B.A., Vandenbosch, B. and Mignerat, M. (2003) Towards the Measurement of Proeess Integration. Scientific Series of CIRANO, Centre Interuniversitaire de Recherche en Analyse des Organisations, Montreal.

[23] Tomanek, D.P. and Schroder, J (2017) Analyzing the Value of Information Flow by Using the Value Added Heat Map. *Proceedings of the* 17*th International Scientific Conference Business Logistics in Modern Management*, Miejsce, 12-13 October 2017, 86.

[24] Parikh, U.B., Das, B. and Maheshwari, R. (2010) Fault Classification Technique for Series Compensated Transmission Line Using Support Vector Machine. *International Journal of Electrical Power & Energy Systems*, **32**, 629-636. https://doi.org/10.1016/j.ijepes.2009.11.020

[25] Kankar, P.K., Satish, C. and Sharma, S.P. (2011) Harsha Fault Diagnosis of Ball Bearings Using Machine Learning Methods. *Expert Systems with Applications*, **38**,

1876-1886. https://doi.org/10.1016/j.eswa.2010.07.119

[26] Ahmad, W.M.T.W., Ghani, N.L.A. and Drus, S.M. (2019) Data Mining Techniques for Disease Risk Prediction Model: A Systematic Literature Review. *International Conference of Reliable Information and Communication Technology*, Johor, 22-23 September 2019, 40-46. https://doi.org/10.1007/978-3-319-99007-1_4

[27] DataFlair (2019) Team Support Vector Machines Tutorial—Learn to Implement SVM in Python. *Data Flair*. https://data-flair.training/blogs/svm-support-vector-machine-tutorial/

[28] Lingitz, L., Gallina, V., Ansari, F., Gyulai, D., Pfeiffer, A., *et al.* (2018) Lead Time Prediction Using Machine Learning Algorithms: A Case Study by a Semiconductor Manufacturer. *Procedia CIRP*, **72**, 1051-1056. https://doi.org/10.1016/j.procir.2018.03.148

[29] Çınar, Z.M., Abdussalam, N.A., Zeeshan, Q., Korhan, O., Asmael, M. and Safaei, B. (2020) Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0. *Sustainability*, ***12***, Article No. 8211. https://doi.org/10.3390/su12198211

[30] Bhavsar, H. and Ganatra, A. (2012) A Comparative Study of Training Algorithms for Supervised Machine Learning. *International Journal of Soft Computing and Engineering*, **2**, 2231-2307.

[31] Osisanwo, F.Y., Akinsola, J.E.T., Awodele, O., Hinmikaiye, J.O., Olakanmi, O. and Akinjobi, J. (2017) Supervised Machine Learning Algorithms: Classification and Comparison. *International Journal of Computer Trends and Technology* (*IJCTT*), **48**, 128-138.

[32] Jensen, F.V. (1996) An Introduction to Bayesian Networks. Springer, New York.

[33] Friedman, N., Geiger, D. and Goldazmidt, M. (1997) Bayesian Network Classifiers. *Machine Learning*, **29**, 131-163. https://doi.org/10.1023/A:1007465528199

[34] Breiman, L. (2001) Random Forests. *Machine Learning*, **45**, 5-32. https://doi.org/10.1023/A:1010933404324

[35] Jhonnerie, R., Siregar, V.P. and Nababan, B. (2017) Comparison of Random Forest Algorithm Which Implemented on Object and Pixel Based Classification for Mangrove Land Cover Mapping. *ICST*, **1**, 292-302.

[36] Goel E, Abhilasha E, Goel E, Abhilasha E (2017) Random Forest: A Review. *International Journal of Advanced Research in Computer Science and Software Engineering*, **7**, 251-257.