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PREDICTION MODEL BEHAVIOR BURNOUT AMONG MANAGERS AND EMPLOYEES OF START-UPS WITH ARTIFICIAL INTELLIGENCE

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ABSTRACT

Employee burnout is a common problem in start-up businesses, and it has a negative impact on the productivity and performance of employees and managers. This study proposes a prediction model based on the Support Vector Machine (SVM) and Gradient Boosting algorithms to identify potential cases of burnout among managers and employees of start-up companies. The model predicts the likelihood of burnout based on data on work-related factors such as workload, job demands, and job control. The performance of the SVM and Gradient Boosting models was evaluated using real-world datasets from startups in predicting burnout cases, according to the results, The proposed model can help managers identify and treat burnout cases early on, resulting in improved employee well-being and overall performance. with the results where age, work experience, job type greatly affects fatigue in the world of work with a sensitivity of 0.91 and a specificity of 0.92.

Keywords: *Prediction; Burnout; Support Vector Machine (SVM); Gradient Boosting; Artificial Intelligence*

1. INTRODUCTION

This research is motivated by the expanding recognition of burnout as a significant problem in the workplace, especially in high-pressure environments such as startup companies. Burnout is a condition marked by physical and emotional depletion that can lead to decreased productivity, absenteeism, and turnover. This can be caused by a heavy burden, job insecurity, a lack of social support, and a poor work-life balance. This study aims to construct a predictive model for identifying burnout risk among new company managers and employees using artificial intelligence techniques [1].

Given the high cost of burnout to individuals and organizations, there is growing interest in developing predictive models to identify at-risk individuals and take preventive action [2], [3]. Artificial intelligence techniques, such as machine learning, are used to develop models in a variety of contexts, including health and finance [4]. Applying these techniques to address burnout issues in startups can provide significant benefits in terms of reducing burnout risk and increasing productivity and overall job satisfaction. Support vector machine and gradient boosting algorithms are utilized in this study. Support Vector Machines (SVM) is an algorithm for supervised learning that can manage both linear and nonlinear classification problems [5], [6]. Working by finding the optimal hyperplane separating data points into different classes, is used to identify individuals at risk for fatigue. Gradient Boosting is an ensemble learning algorithm combining several weak models to create a strong predictive model. It is well suited for handling complex relationships between input features and target variables and can handle categorical and numeric features [7], [8].

2. RESEARCH METHOD

Using artificial intelligence techniques, construct a predictive model of behavioural fatigue among managers and start-up employees. Several steps were taken, including a review of the literature on behavioural fatigue, its causes, symptoms, and effects, as well as studies on prediction models and artificial intelligence that were pertinent to the topic. This assists in establishing the research background and context, identifying research gaps, and emphasizing the significance of the proposed research [9]. The collected information consists of survey responses, psychological assessments, performance indicators, and other pertinent metrics pertaining to fatigue and job factors. The data capture procedure adheres to ethical guidelines, ensuring the confidentiality and anonymity of participants [10].

With predictions of behavioral saturation, feature selection is performed. Personal characteristics, work-related factors (e.g., workload, job demands, and job resources), organizational factors, and psychological factors (e.g., stress levels) are examples of characteristics [11].

The analysis of the prediction model's results interprets the importance of various features in predicting satiation behaviour and identifies significant factors contributing to fatigue among startup managers and employees. The research stages can be seen in Figure 1.

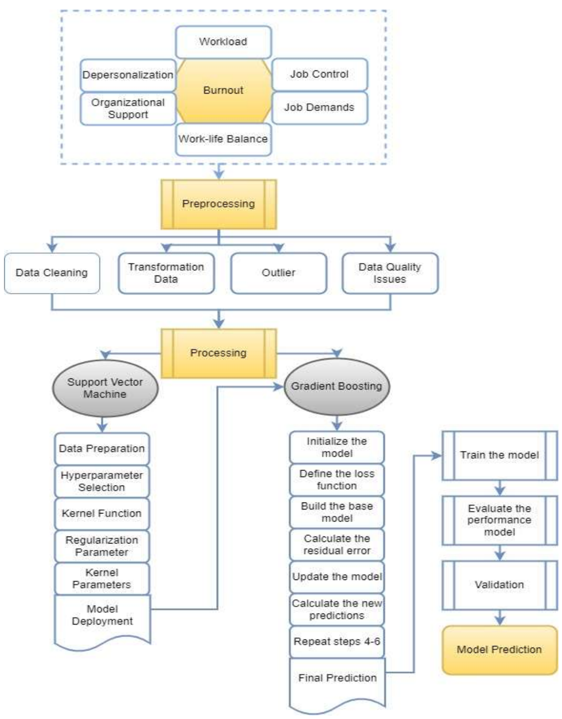

Figure 1. Research Stages

2.1. Burnout

Burnout is a state of emotional, physical, and mental exhaustion brought on by protracted and excessive stress. It is typically related to work or job-related factors, such as a heavy burden, a lack of control, and inadequate resources. Burnout can be detrimental to a person's health, productivity, and well-being. Common symptoms of burnout [12] include fatigue, irritability, insomnia, decreased performance, and feelings of detachment from work or colleagues. Burnout can affect anyone, but it is notably prevalent in industries with high levels of stress, such as healthcare, finance, and technology. shown in figure 2.

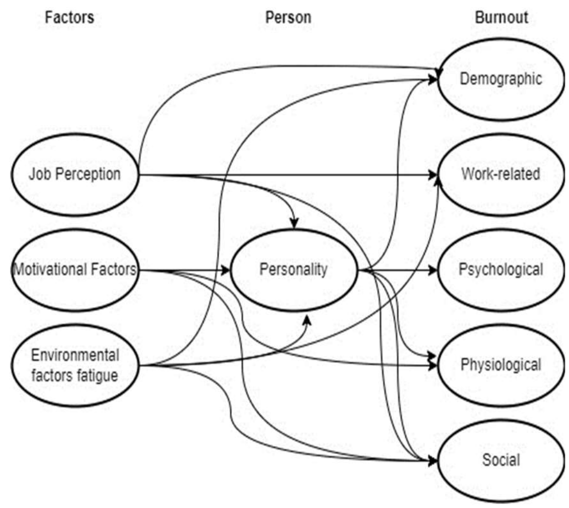

Figure 2. Burnout Cycle

2.2. Support Vector Machine (SVM)

SVM is an algorithm for machine learning used for classification and regression analysis. It has gained popularity due to its capacity to manage high-dimensional data and its proficiency with linearly discrete data sets. SVM seeks to identify the hyperplane that maximizes the distinction between two classes. SVM determines the weight vector and bias term of the hyperplane by using a kernel function to map input data to a higher-dimensional space. When classifying new data points, weight vectors are utilized.

The optimization problem can be formulated as follows [13]:

$$minimize = \frac{1}{2\|w\|^2}$$
$$Subject\ to : y_{i(\mathrm{w}^{\mathrm{T}}x_i+b)} \geq 1, for\ all\ i \quad (1)$$

Where y_i is the class label for the $i-th$ instance, x_i is the fit input feature vector, w is the weight vector, b is the bias term, and $2\|w\|^2$ is the squared norm of the weight vector.

The goal of the optimization problem is to minimize the weight vector's squared norm, thereby maximizing the margin between the two classes. Constraints ensure that the hyperplane correctly classifies all data points.

The Lagrangian of the optimization problem can be defined as follows [14]:

$$L(w, b, alpha) = \frac{1}{2\|w\|^2} - \text{sum(alpha i} * \left[y_{i(w^T x_i + b)} - 1\right]) \quad (2)$$

Where $alpha_i$ is the multiplier Lagrange associated with the constraint. Setting the partial derivatives of the Lagrangian with respect to w and b to zero then yields the optimization problem's solution [15]:

$$w = sum(alpha_i * y_i * x_i) \\ sum(alpha_i * y_i) = 0 \quad (3)$$

The supporting vectors, which are the data points closest to the hyperplane with a nonzero Lagrange multiplier, are then utilized to compute the weight vectors and bias terms. The classification function for the newly collected data points can then be specified as [16]:

$$f(x) = sign(w^T x + b) \quad (4)$$

2.3. Gradient Boosting

Gradient Boosting is a machine learning classification and regression algorithm. The ensemble method combines a number of poor students to form a group of strong students. Gradient Boosting is a powerful algorithm for handling intricate nonlinear relationships between input features and target variables [17].

The essence of gradient enhancement is fitting a weak model to the remnant of the prior model. At each step t, the model update formula is [18]:

$$F_{t(x)} = F_{\{t-1\}\{x\}} + h_{t(x)} \quad (5)$$

where $F_{t(x)}$ is the model upgraded at step t, $F_{\{t-1\}\{x\}}$ is the model at step $t-1$, and $h_{t(x)}$ is the weak model to fit at step t.

Weak model $h_{t(x)}$ is chosen to minimize the loss function [19].

$$L(y, F_{\{t-1\}(x)} + h_{t(x)}) \quad (6)$$

where y is the target variable and L is the loss function, which can be either mean squared error or lost logs. The loss function quantifies the gap between the predicted and actual value.

The $h_{t(x)}$ typically, a feeble model is a decision tree with a shallow depth and few leaf nodes. The tree is fitted to the residual negative gradient of the loss function from the prior model.

The final model is the sum of the weak models weighted by learning rate [20]:

$$F(x) = sum(eta * h_{t(x)}) \\ for\ t = 1\ to\ T \quad (7)$$

where T is the total number of weak models

3. RESULT AND DISCUSSION

Regarding gender, recent analyses of the relationship between gender and burnout have led to the widespread perception that female employees are more likely than male employees to experience burnout, as women are slightly more emotionally exhausted than men. Unlike males, women are less impersonal. The initial analysis used both masculine and female data [21]. as shown in table 1 and table 2 displays variables or characteristics used for data processing. [There is an attached table 1 and 2].

Support Vector Machines (SVM) perform the burnout prediction classification assignment. including personal characteristics, work-related factors, organizational factors, and psychological factors in the processing of behavioural fatigue data. SVM model training utilizing linear kernel functions based on data characteristics [22]. The SVM model identifies the hyperplane that most effectively separates the data elements. Prediction results can be seen in table 3. [There is an attached table 3].

Gradient Boosting Training models utilize a training apparatus. To optimize model performance, define hyperparameters, learning rate, number of estimators, and maximal tree depth. The model builds a decision tree sequentially, with each successive tree being trained to correct errors made by the prior tree [23]. The results can be seen in table 4. [There is an attached table 4].

Examine the model output for significant factors that contribute to behavioral exhaustion in Model Interpretation. Analysis of the Gradient Boosting model's feature importance scores to determine the most influential features for predicting saturation [24], [25]. Improving the accuracy and interpretability of model predictions by optimizing the model by modifying hyperparameters or implementing feature engineering. Can be seen in figure 4.

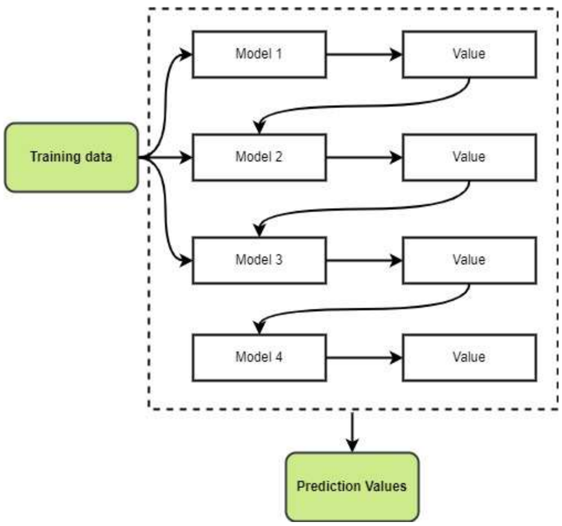

Figure 3. Prediction Workflow

As in figure 4, to investigate the unique relationship between work and burnout, a regression analysis was performed. In the first model, model 1 investigates the effect of age and education; model 2 investigates workload; model 3 investigates the level of emotional intelligence; and model 4 investigates psychological factors. The following is an analysis of each model:

- **Model 1**

It has been discovered that demographic factors such as age, gender, and level of education are associated with exhaustion. Younger employees and those with lower levels of education, for instance, may be more susceptible to exhaustion due to job insecurity and lack of support. Can be seen in figure 3.

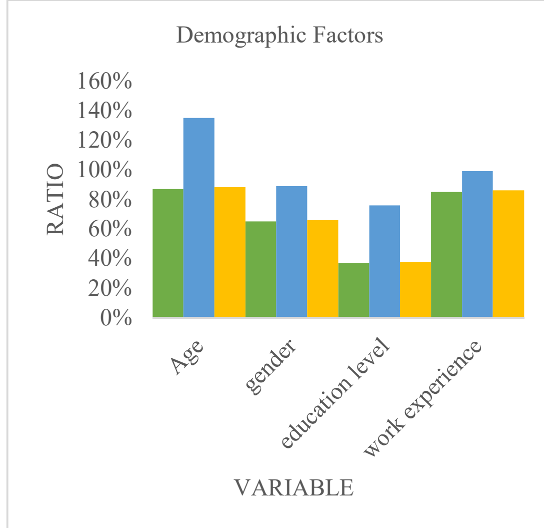

Figure 4. Demographic Factors

- **Model 2**

Work-related variables, including workload, job demands, and job control, were also identified as significant predictors of exhaustion. High levels of job demands and low levels of job control significantly increase the risk of fatigue among workers. Can be seen in figure 4.

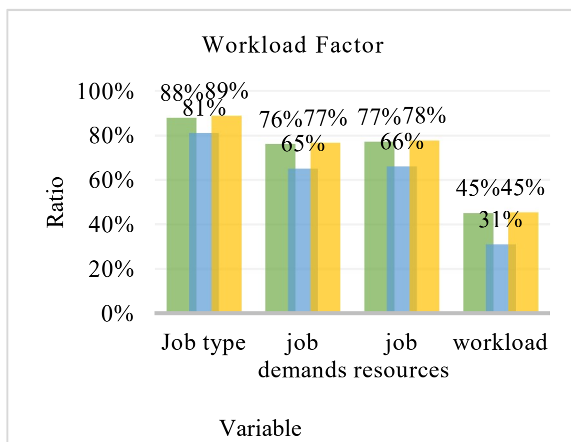

Figure 5. Workload Factor

- **Model 3**

Those with a high level of emotional intelligence, which refers to the capacity to perceive and manage one's own emotions and the emotions of others, typically do not experience fatigue. Lack of emotional support from coworkers or superiors can make it more challenging to manage stress and increase the risk of burnout, and negative emotions such as frustration, wrath, or anxiety can also cause burnout. Can be seen in figure 5.

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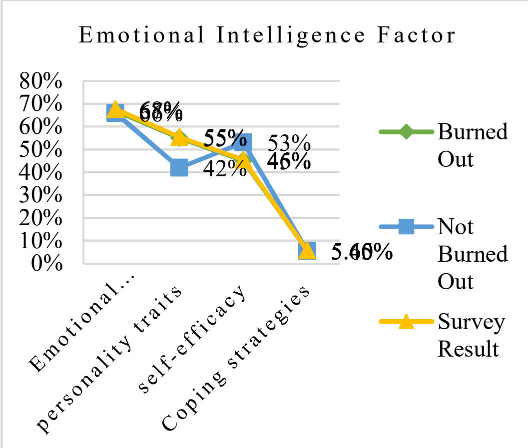

Figure 6. Emotional Intelligence Factor

- **Model 4**

Stress, coping strategies, and personality traits have also been found to be associated with fatigue. Employees with elevated stress levels and ineffective coping mechanisms are more likely to experience burnout. Furthermore, personnel with particular personality traits, such as neuroticism or low self-esteem, may be more susceptible to burnout. Can be seen in figure 6.

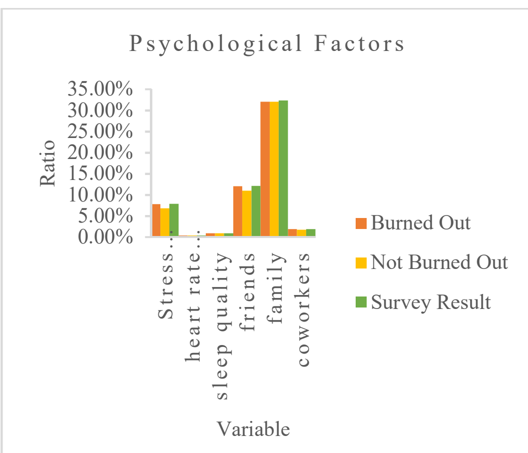

Figure 7. Psychological Factor

3.1. Evaluation

Sensitivity and specificity are two common performance metrics for binary classification models [26]-[28]. Specificity measures the proportion of genuine negatives, or the proportion of correctly identified class 0 samples. Sensitivity quantifies the proportion of true positives, or the proportion of class 1 that was correctly identified. The equations for specificity and sensitivity can be written as follows [29], [30]:

$$Specificity\ (\%) = \frac{TN}{TN + FP}\ x\ 100$$
$$Sensitivity\ (\%) = \frac{TP}{TP + FN}\ x\ 100 \quad (8)$$

The predictive model for behavioural fatigue achieved a sensitivity of 0.91, indicating that it correctly identified 91% of the actual positive cases, and a specificity of 0.92, indicating that it correctly identified 92% of the actual negative cases. Evaluation results can be seen in table 5. [There is an attached table 5].

4. CONCLUSION

This study involved data on various demographic, work-related, psychological, physiological, and social factors associated with fatigue. SVM and Gradient Boosting algorithms can be used to analyse data and develop predictive models that identify individuals at risk for burnout. This research has the potential to provide valuable insight into the factors that contribute to burnout in the start-up environment and help identify effective interventions to prevent burnout. Using AI techniques, this study was able to identify complex relationships between various factors. Overall, it provides practical insights for start-up organizations to improve the well-being and productivity of their employees. The predicted results achieved can be seen in table 6, where age, work experience, job type greatly affect fatigue in the world of work with a sensitivity of 0.91 and a specificity of 0.92.

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Table 1. Regarding gender

Gender	Number (Person)	Age	Marital Status	
			Married	Single
Woman	667	25-49	435	232
Man	873	27-55	662	211
Total	**1.540**	**30-50**	**1.097**	**443**

Table 2. Feature Variables Used

Variables or Features Used				
Demographic	**Work-related**	**Psychological**	**Physiological**	**Social**
Age	Job Type	Emotional Intelligence	Stress Hormones	Friends
Gender	Job Demands	Personality Traits	Heart Rate Variability	Family
Education Level	Job Resources	Self-Efficacy	Sleep Quality	Co-workers
Work Experience	Workload	Coping Strategies		

Table 3. Predictive Performance on Parameters in SVM

Parameters	Training Data	
	Total Number	Ratio
a = 1		
1	1457	53.12
10	1425	51.26
20	1372	42.46
25	1263	32.35
30	1253	31.63
40	1526	55.36
50	1526	53.56
85	1652	53.56
100	1352	41.26
b = 20		
1	1425	51.46
10	1424	51.45
20	1252	32.16
25	1536	55.26
30	1526	54.37
40	1426	50.26
50	1324	43.26
85	1525	55.26
100	1252	31.36
c = 35		
1	1235	30.16
10	1526	54.47

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20	1626	56.26
25	1152	30.36
30	1623	56.61
40	1525	51.36
50	1162	30.25
85	1627	56.26
100	1152	30.16
d = 50		
1	1425	50.36
10	1253	32.37
20	1263	32.45
25	1253	32.37
30	1252	32.36
40	1263	32.45
50	1536	51.37
85	1653	55.37
100	1263	32.45
e = 100		
1	1627	55.36
10	1435	43.62
20	1542	51.63
25	1542	51.63
30	1262	32.76
40	1162	31.36
50	1253	33.27
85	1433	41.63
100	1253	32.34

Table 4. Outcome Definition Gradient Boosting

Outcome Definition	
Training	0.94%
Testing	0.91%
Validation	0.89%

Table 5. Table of Sensitivity and Specificity

Score Range	Sensitivity	Specificity
50:50	0.75	0.77
60:40	0.85	0.82
70:30	0.91	0.92
80:20	0.89	0.88

Table 6. Prediction Result

Variables	**Burned Out**	**Not Burned Out**	**Survey Result**
Age	87%	135%	88%
Gender	65%	89%	66%
Education Level	37%	76%	38%
Work Experience	85%	99%	86%
Job Type	88%	81%	89%
Job Demands	76%	65%	77%
Job Resources	77%	66%	78%
Workload	45%	31%	45%
Emotional Intelligence	67%	66%	68%
Personality Traits	55%	42%	55%
Self-Efficacy	45%	53%	46%
Coping Strategies	5,60%	5,40%	5,65%
Stress Hormones	7,80%	6,80%	7,87%
Heart Rate Variability	0,35%	0,33%	0,35%
Sleep Quality	0,88%	0,87%	0,89%
Friends	12%	11%	12%
Family	32%	32%	32%
Co-workers	1,90%	1,70%	1,92%