PREVALENCE AND ASSOCIATED FACTORS OF DEPRESSION AMONG MALAYSIAN ELDERLY USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Depression disorders are becoming acknowledged as substantial contributors to worldwide morbidity. In the majority of Asian studies, the prevalence of depression among the elderly ranged from 3.7% to 36.7%, with Malaysia having the highest prevalence at 27.8%. This research aims to use machine learning approaches to uncover the major factors related with depression in the older population of Malaysia, as well as the effect of depression on the occurrence of severe injuries. The study includes a sample of 3,772 Malaysians aged 60 and older from the 2018 National Health and Morbidity Survey (NHMS) collected by the Institute of Public Health (IPH). 5.75 percent of the elderly (60 years and older) sampled experienced depression. Three machine learning techniques, namely Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Random Forest (RF), were applied, and their classification performance was compared using precision and Area Under ROC Curve (AUC). SVM outperformed the other two machine learning algorithms since its precision and AUC value were greater than those of the other two (74.6 percent and 0.759, respectively). According to the results of the SVM, social support had a substantial effect on depression and hypertension among the elderly. Other factors that influence the development of depression in the elderly include sociodemographic characteristics and the presence of health issues such as hypertension or obesity. In addition, comparing elderly people with and without anxiety, depressed seniors are 1.75 times more likely to sustain a serious injury. Hence, this study would contribute to public health by identifying the factors contributing to depression among the elderly so that the community, government, and public health specialists could adopt effective methods to combat depression, if social support from the immediate family is not available to safeguard the safety of our elderly.

Keywords: Depression, elderly, machine learning.

INTRODUCTION

The World Health Organization (2021) defines depression as a mood disorder, and it is no longer considered a rare disease in the field of mental illness. Mental distress affects approximately 300 million people worldwide (WHO, 2021). It is identified as a global public health concern as it increases healthcare spending and mortality rates (Gold et al., 2020). The data from 2015 (Pulse TMS, 2021), China, India, and the United States had the highest rates of depression. Based on the World Health Organization (2017) report, those aged 60 and older account for 5.7% of global depression prevalence, and that percentage is expected to rise between 2015 and 2050, when the population is expected to grow from 900 million to 2 billion. The majority of Asian studies found that 3.7% to 36.7% of the elderly had a greater frequency of depression (Krishnaswamy et al., 2012; Luppa et al., 2012; Zenebe et al., 2021). Depressive disorders were most common among the elderly in Asian countries, with Sri Lanka (27.8%), Indonesia (33.8%), Japan (30.3%), Vietnam (17.2%), India (12.7%), and Malaysia (27.8%) having the highest prevalence (Mirkena et al, 2018; Pramesona & Taneepanichskul, 2018). According to Vanoh et al. (2016), depression affects 16.5% of senior Malaysians. Furthermore, as per Malaysian ethnogroups, 30.0% of the Malay elderly population was depressed (Abdul Rashid Khan et al., 2012). Even more shocking, Rodda et al. (2011) discovered that many older people failed to recognise the symptoms of depression.

Depression can lead to disruptions and low life production, which can affect relationships and cause some chronic diseases, according to Beck et al. (2011). In the worst-case scenario, depression could result in suicide. More than 800,000 individuals commit suicide each year (WHO, 2021). Given the severity of depression's effects, it is essential to undertake effective measures to lower the rate of depression among the elderly as much as is feasible. Therefore, it is vital to examine the potential indicators of this problem, particularly with regards to the elderly. Several national studies on depression among the elderly discovered that the most important predictors were lifestyle habits (physical activity, smoking), demographic characteristics (income, age, family size, gender, and ethnicity), and self-reported chronic disorders (Gautham et al., 2020; Kader Maideen et al., 2014; Krishnaswamy et al., 2012).

On the other hand, early identification of potential depression factors associated with the older population is crucial towards improving quality of life. Machine learning techniques have been employed in numerous international studies to forecast and investigate the major risk factors for this mental health condition. To develop the most precise models for predicting depression in the elderly population, the majority of global research has also employed machine learning techniques such as Lasso logistic regression, random forest, support vector machine, and artificial neural network (Su et al., 2021; Seo et al., 2020; Kim et al., 2019; Sau and Bhakta, 2017).

Recent studies have also shown that depression has a lot of negative effects on the elderly. And to make matters worse, most of us think that physical infirmity rather than depression is what causes depression in the elderly, which carries a far higher risk of negative consequences. Numerous studies have revealed a link between depression, the likelihood of injury, and the common consequences of falls in the elderly (Joseph et al., 2019; Sween et al., 2019; Mishra et al., 2017). Numerous studies have shown that one of the most prevalent adverse effects of depression is injury (Yeong et al., 2016; Hajek & König, 2017).

Concerned about the alarming rise in depression among Malaysia's elderly population, effective steps need to be taken to address the risk factors for depression. Poor mental health could also lead to poor physical health and misjudgments. This is especially true when depression is present. In most of the national studies on depression among the elderly, the approach taken by using machine learning techniques in identifying risk factors associated with the prevalence of depression among the Malaysian elderly is still lacking, and for the time being, there is less study relating to depression among the elderly and its consequences, such as injuries. The technique of multivariate logistic regression was used in the majority of studies on depression status in the elderly and its associated risk factors. Though multivariate logistic regression can be considered one of many predictive modelling techniques, the scope of machine learning techniques covers a lot more. In order to fill this gap, this study will use a number of MLT techniques to try to predict the occurrence of depression and find out if there is a link between depression and serious injuries in the elderly of Malaysia.This study will use algorithms called Support Vector Machine, Random Forest, and Neural Networks to learn more about the factors that place individuals at risk for depression, especially the elderly.

PREDICTION OF THE ELDERLY'S DEPRESSION

There have been more international studies on predicting elderly depression using machine learning techniques (MLT) as well as the identification of the most important predictors of depression in the elderly. Su et al. (2021) used MLT to forecast depression in China's elderly population. Support Vector Machines, Random Forest, Gradient-Boosted Decision Tree, Deep Neural Network, and Logistic Regression with Lasso Regularization were all used in their study, and their findings on the most important predictors of mortality for the depressed elderly in China were daily living activities, self-rated health, marital status, arthritis, and the proportion of cohabiting couples. Seo et al. (2020) used Random Forest to construct predictions and found that ratings for cognitive ability, quality of life, and home background had the biggest effects on elderly Koreans with depression. Moreover, Na et al. (2020) used MLT to investigate how the tree-based ensemble technique and random forest could be used to predict future depression in elderly Koreans. This study found that family income, family ties, satisfaction with leisure activities, and social relationships in general were all strong predictors of depression among Korean seniors.

Multivariate logistic regression and multiple linear regression have been used in the vast majority of national studies to figure out how likely it is that older Malaysians will be depressed. Leong et al. (2020) conducted research at a childcare centre for the elderly, using multivariate logistic regression to investigate whether or not there was a connection between various demographic characteristics and depression. Both Ahmad et al. (2020) and Azniza et al. (2019) used the same technique in their research to study the factors that lead to depression in Malaysians who are in their senior years. Multiple linear regression was used by Hamid et al. (2019) to discover the characteristics that lead to depression in senior Malaysians who have undergone important life events. However, the MLT technique has not been utilised in any of the national studies that have been conducted in Malaysia with the purpose of predicting depression among the older population.

In conclusion, many MLT methods have been employed in research globally to predict elderly depression, including Decision Tree (DT), Deep Neural Network (DNN), Logistic Regression (LR), LR LASSO Regression, Random Forest (RF), Support Vector Machine (SVM), and others. However, the use of MLT in Malaysia is lacking. In addition, in most of the studies, age, gender, marital status, income, and health were all found to be important predictors of depression in the elderly.

IMPACT OF DEPRESSION TOWARDS THE INJURY

One of the main factors contributing to public health issues related to the elderly globally is injuries (Yoo et al., 2016). The probability of suffering an injury may be increased by excessive anxiety or sadness (Iaboni & Flint, 2013). Everyone can sustain injuries from falling, but seniors are more likely to fall and get hurt as a result. According to research by Hajek and Konig (2017), senior injury rates were correlated with fall incidents. Additionally, Vu et al. (2018) discovered a link between a senior's risk of falling and their likelihood of experiencing depressive symptoms (OR: 5.50; 95% CI: 1.88-16.50). Hajek and König (2017) found that 17.6% of patients in Germany between the ages of 40 and 95 fall every year, while Yeong et al. (2016) found that 4.7% of people aged 60 and older in rural Perak, Malaysia, fall every year.

The biggest cause of injuries among the elderly, according to the Malaysian Ministry of Health (2018), is outdoor falls, and more than 30% of the victims, have had two or more falls. However, the majority of older people chose to self-treat rather than seek medical attention following a fall (Stewart et al., 2015; Gilasi et al., 2014). Because it has led to a variety of ailments, including abrasions, fractures, brain haemorrhage, and musculoskeletal disability, injury in the elderly should be taken seriously (Dhargave and Sendhilkumar, 2016). It's crucial to determine whether depression significantly affects older Malaysians' injuries so that we may learn more about them and prevent them from getting worse. This will enable us to comprehend how to prevent injuries from deteriorating further..

METHODOLOGY

Secondary data from the 2018 National Health and Morbidity Survey (NHMS), which comprised 3,772 Malaysians aged 60 and over, were used in this study. The main factors examined in this study were demographic (age, class, gender, marital status, employment status, and education level), non-communicable diseases (diabetes, hypertension, and hypercholesterolemia), social relationships (abuse, lack of social support), and dietary status (body mass index, abdominal obesity). The dependent variable was the Geriatric Depression Scale's (GDS) measure of the prevalence of depression among older adults in Malaysia. Exploratory data analysis (EDA) is used to deal with missing values, imbalanced data, attribute selection, transformation, and validation. This is done so that the data can be used by machine learning algorithms.

This study's design made use of the CRISP-DM approach, which is well-known in the data mining industry. The six phases of the CRISP-DM include business understanding, data preparation, data understanding, modelling, model evaluation, and model deployment.Three machine learning techniques were applied in this study and each one of the techniques were explained below.

Random Forest (RF)

RF is well-known as a popular algorithm that builds a random decision tree in each iteration of the bagging algorithm and always makes good predictors. The idea for the RF classifier came from a decision tree (DT). Each of the classifiers in the RF was a DT classifier, so the group of classifiers was called a "forest" (Mantas et al., 2019). For more information, the RF assembly trees were constructed and trained on bootstrapped subsets. Predictions were made by following the tree's branches according to the rules for splitting and evaluating the leaf as well. A node in a tree remained for a splitting rule for a particular attribute. Only a subset of attributes, which were specified by the subset ratio criterion, were taken into account when choosing the splitting rule. This rule has separated the values in a way that works best for the chosen parameter criterion, and it has also separated the values into their own classes. Then, the process of building new nodes was repeated until the stopping criteria were met. For prediction, each DT was used on the test set to look at the error, and the final classification decision will be based on the majority vote on all DT.

Support Vector Machine (SVM)

SVM is a method for the classification of both linear and nonlinear data into groups. The goal of SVM is to find the optimal hyperplane that divides the data points into two parts by making the margin as big as possible. In this study, linear SVM was used to try to predict depression in older Malaysians. All of the data points and vectors were turned into points in space and classified into two distinct groups by leaving a clear gap as wide as possible between them. This was done so that a straight line could be drawn in that two-dimensional plane. Then, new data points or vectors were placed in the same space and predicted to belong to a category based on which side of the gap they fell on. The vectors that are closest to the hyperplane and that affect the position of the hyperplane were termed support vectors (Rithesh, 2017).

Artificial Neural Network (ANN)

ANN is like the human brain in that it has artificial neurons and links between them (al Rashid Agha et al., 2018). The connections between the units are weighted. Each neuron will use its axon terminals to try to stimulate other neurons and tell which terminals are active and which ones should stay. Simply put, ANN will attempt to create a function that maps the input to the desired output. The model was learned by using a back propagation algorithm called Multi-Layer Perceptron (MLP) to train a feed-forward neural network.

Model Evaluation

For model evaluation in CRISP-DM, the best model for predicting the reaction to depression among older Malaysians was chosen based on the classification performance of the model. On the basis of model classification performance, each model was evaluated based on its accuracy, precision, sensitivity, specificity, receiver operating characteristics (ROC) Chart, and area under the ROC curve (AUC).

RESULTS AND DISCUSSION

Tables 1 and 2 summarise the data set used for analysis in this study. A total of 3772 elderly Malaysians, aged 60 years and older, took part in the national survey, and 217 (5.75%) were found to be depressed, while 3,555 (94.25%) were not. According to strata data, 1,601 seniors (42.44%) live in urban areas, while 2,171 seniors (57.56%) live in rural areas. There were 1,988 elderly females (52.70%), and 1,784 senior males (47.30%). The majority of seniors (2,525; 66.94%) were married, followed by the widowed (1,106; 29.32%), the never-married (82; 2.17%), and the divorced (59; 1.56%). Only 1,017 (26.06%) of all elderly people were working, while 2,755 (74.04%) were unemployed. 48.78% (1,840) have only completed elementary school, 25.19% (950) have some college, 19.25% (726) have no college, and 6.70% (256) have completed graduate or professional studies.

There were 2,503 (66.36%) more seniors with abdominal obesity than without abdominal obesity (1,269). There were 3,471 seniors (92.02%) who had no history of abuse and 301 (7.98%) who did. The elderly received low-to-fair social support from 1,154 (30.59%), strong social support from 1,402 (37.17%), and very high social support from 1,216 (32.24%). There were 95 more senior citizens (2.52 percent) who sustained serious injuries than those who sustained minor injuries (3,677 people, or 97.48 percent). The average weight difference between those with and without diabetes mellitus was 2,805 (74.36%) and 967 (25.64%), respectively. Furthermore, 48.57 percent of the 1,832 senior citizens tested were found to be hypertension-free, while 51.43 percent were found to have hypertension. A total of 2,258 elderly people (59.86%) did not have hypercholesterolemia, while 1,514 (40.14%) did. The elderly had a mean body mass index of 25.58 kilogrammes per square metre with a standard deviation of 4.

Table 1: Summary Statistics for Discrete Variables

Variable	Descriptions	Percentage (%)
Depression	Normal	94.25
	Depressed	5.75
Strata	Urban	42.44
	Rural	57.56
Gender	Male	47.30
	Female	52.70
Marital status	Never married	2.17
	Married	66.94
	Separated/Divorced	1.56
	Widowed	29.32
Employment	Employed	26.96
	Unemployed	73.04
Education level	No formal education	19.25
	Primary education	48.78
	Secondary education	25.19
	Tertiary education	6.79
Obesity	No abdominal obesity	33.64
	Abdominal obesity	66.36
Abuse	No	92.02
	Yes	7.98
Social support	Low to fair	30.59
	High	37.17
	Very high	32.24
Type injury	Minor injury	97.48
	Severe injury	2.52
Diabetes mellitus	No	74.36
	Yes	25.64
Hypertension	No	48.57
	Yes	51.43
Hypercholesterolemia	No	59.86
	Yes	40.14

Table 1: Summary Statistics of Dataset for Continuous Variables

Variable	Mean (±Std. Deviation)	Min	Max
Age	68 (± 6.64)	60	99
BMI	25.58 (± 4.72)	11.96	48.17

Factors contributed to depression among elderly Malaysians

Table 3 shows the summary of the significant variables that give a huge contribution to the depression among Malaysian elderly for each model.The results show that all of the predictive modelling indicated that social support had a significant role in the development of depression among the senior population in Malaysia. Diabetes mellitus was the least important predictor of depression in Malaysia's older population, according to Random Forest and Strata, as determined by Support Vector Machine and Artificial Neural Network. However, because SVM was the best model for predicting depression among Malaysian elderly, this study highlighted the most and least important SVM predictors that contributed to depression among Malaysian elderly. SVM has shown that social support was a huge contributor to the Malaysian elderly's depression, with a value of 29%.

Table 3:Summary of Most and Least Important Predictor by SVM, ANN and RF

Model	Most Important Predictor	Least Important Predictor
Random Forest	Social Support	Diabetes Mellitus
Support Vector Machine	Social Support	Strata
Artificial Neural Network	Social Support	Strata

Model Evaluation

Table 4 presents RapidMiner's performance results for each of the predictive models. In terms of accuracy, RF performed the best, followed by SVM and ANN, with respective scores of 68.45% and 65.6%. Aside from that, SVM had the highest precision rate (74.56%), followed by RF (71.89%) and ANN (65.36%). Based on sensitivity performance, RF had the highest rate at 72.40 percent, suggesting that 72.40 percent of senior Malaysians with depression were correctly identified as depressed. In comparison to other models, SVM has the highest performance rate in terms of specificity, at 79.65%. According to SVM, 79.65% of senior Malaysians without depression were correctly classified as "normal" for depression status. The AUC value suggests that SVM had the best AUC performance, with a value closest to 1 of 0.759, followed by RF (0.739) and ANN (0.712). As shown in Figure 1, the blue line (SVM), the green line (ANN), and the red line (RF) represent the performance of ROCs for each of the prediction models. The higher the line is positioned relative to other lines, the better the model's performance in terms of ROCs. The graph indicates that SVM performed the best among ROCs, followed by RF and ANN. In this study, SVM proved to be the best machine learning technique (MLT) for predicting depression among the elderly in Malaysia.

Table 4: Performance Results for Predictive Modeling

Measurement	RF	SVM	ANN
Accuracy (%)	71.90	68.45	65.67
Precision (%)	71.89	74.56	65.36
Sensitivity (%)	72.40	57.16	67.34
Specificity (%)	71.42	79.65	64.14
AUC	0.739	0.759	0.712

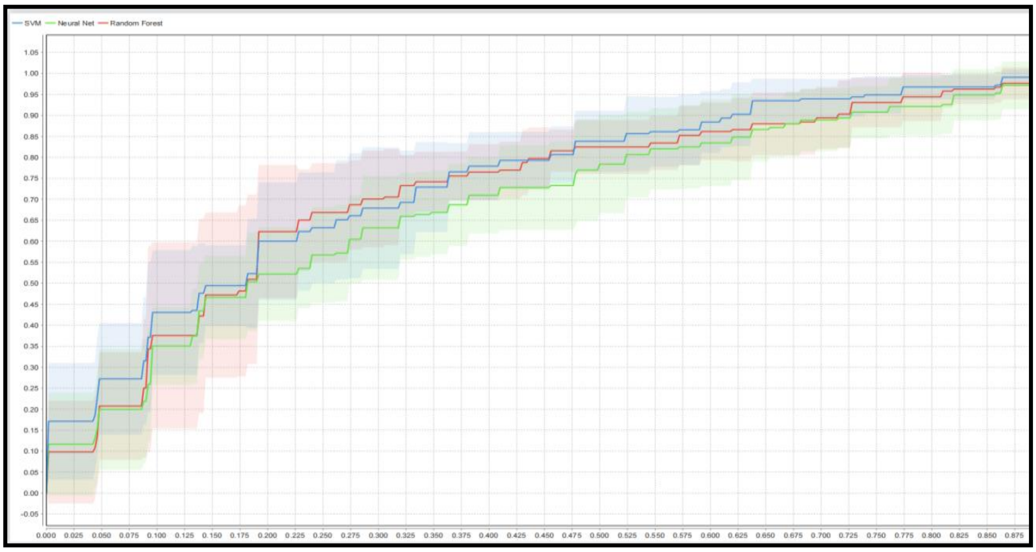

Figure 1: ROC Charts for SVM, ANN and RF

Deployment of the Best Prediction Modeling

In the preceding section (Model Evaluation), we determined that Support Vector Machine (SVM) was the best effective and efficient machine learning technique for our research. Operator Explain Predictions based on SVM were used to determine the relative importance of many parameters in the prediction of depression in the older population of Malaysia. Figure 2 provides more information about the percentage distribution of depression predictors. The range of possible causes of depression among Malaysian elderly is shown by the range of colours assigned to the different weight values. Social support (29%) played an important role in depression among the elderly, followed by hypertension (14%), obesity (13%), education level (9%), abuse (9%), employment (9%), gender (7%), hypercholesterolemia (3%), body mass index (2%), and age (2%). Each of diabetes mellitus, being married, and social class only added 1% to the number of elderly people in Malaysia who were depressed.

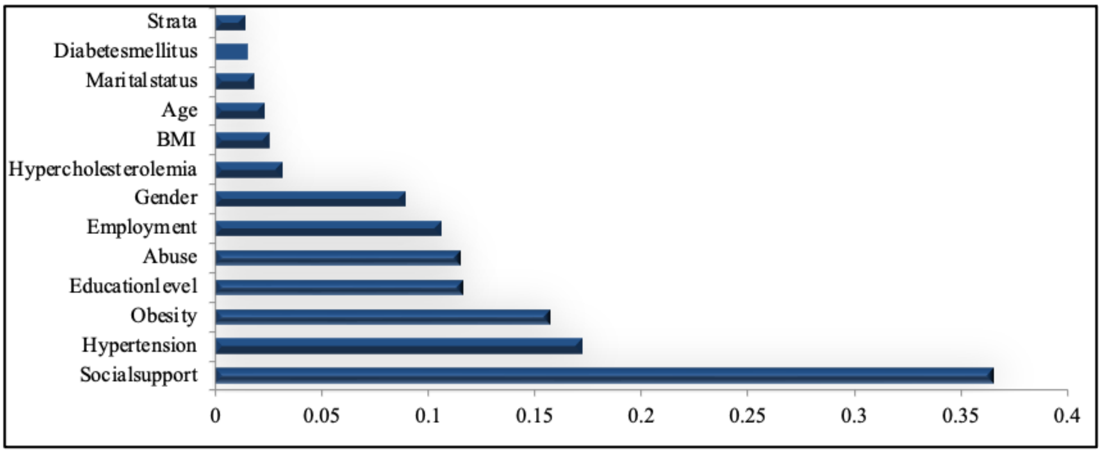

Figure 2: Percentage Contribution of the Predictors by Using SVM Model

The effect of depression on the occurrence of the injury

Table 4 displays a cross-tabulation of depression and injury severity. The table shows that 2.40% of elderly people without depression and 4.10% of depressed senior people suffered severe injuries. This shows that, compared to normal elderly people without depression, those who were depressed had a higher risk of experiencing a serious accident. Both the risk and odds ratios are greater than one. Approximately 4.1% of the depressed elderly had severe injuries, compared to only 2.4% of the normal elderly, indicating that it is 1.71 times more likely for depressed older people to suffer a serious accident than for ordinary senior people without depression. In terms of the odds ratio, the odds of an elderly person with depression suffering a severe injury are 1.75 times higher when compared to those who are normal.

Table 5: Odds ratio estimation on injury severity due to depression

Depression Status	Severity of Injury		Total
	Severe	Minor	
Depressed	9 (4.1%)	208 (95.9%)	217
Normal	86 (2.4%)	3469 (97.6%)	3555
Risk ratio	1.714		
Odds Ratio	1.754		

CONCLUSION

The frequency of depression among elderly Malaysians is 5.75 percent. The classifier model comprised of Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) has been used to predict the prevalence of depression among the elderly in Malaysia. In order to determine the best model among the other machine learning models, classification performance was used to evaluate the models. This study revealed that SVM was superior to other models for predicting depression among the elderly in Malaysia because of its greater precision, specificity, and second-largest AUC. This finding was supported by Nusinovici et al. (2020) and Rithesh (2017), who also found that the SVM was superior to other prediction models. The best model evaluated by performance metrics revealed social support to be the most influential predictor of depression among the elderly in Malaysia. This finding was supported by Sathya and Premkumar (2020), Chen et al. (2019), and Mohd et al. (2019), who all found a strong link between social support and depression in the elderly.

The extensive secondary data from the 2018 National Health and Morbidity Survey (NHMS) that was used in this study and covered the older population in Malaysia offers a variety of uses as well as constraints. To begin, the respondents were responsible for their own self-reporting of numbers, which could have resulted in reporting bias. Second, the data limit the researcher's ability to investigate other potential risk factors for depression in the older population of Malaysia, such as family history, personality traits, social media, and others. These risk factors include, but are not limited to, social media, personality traits, and family history. It is difficult for the researcher to do a comparative study because there is not enough previous research on geriatric depression that uses Machine Learning Techniques (MLT). It is advised that additional MLT be utilised for the purposes of future prediction. Some examples of these MLT include Naive Bayes, Discriminant Analysis, and Deep Neural Networks. It is strongly advised that the Ministry of Health Malaysia and other public health professionals put into practise the findings of this study in order to treat depression disorders that are prevalent among older people in Malaysia. Through the use of a "big data" approach, sharing the results of this study may also encourage more research into how MLT can be used in many other fields besides the healthcare industry.

It is fervently hoped that the findings of this study will assist in the implementation of effective strategies in the handling of depression problems among the elderly in Malaysia. In particular, it is hoped that the findings of this study will assist stakeholders, health care policymakers, and public health providers. The findings of this study can also be used to create and increase awareness among all of us to be on the lookout for and take action to eliminate the significant risk factor of depression among the elderly in Malaysia. This can be done by using the findings to create and increase awareness that we should all be alert and take action. The application of Machine Learning Techniques, often known as MLT, can be useful when dealing with classification and prediction issues. It is sincerely hoped that the findings of this study may assist stakeholders, health care policymakers, and public health professionals in Malaysia in implementing effective approaches for the purpose of alleviating depression among older adults. The findings of this study can also be used to raise awareness about the significant risk factor for depression among Malaysia's older population and to inspire all of us to take action toward addressing this problem.

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