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A Study on the Correlation Between Hand Grip and Age Using Statistical and Machine Learning Analysis

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Abstract: Handgrip strength (HGS) is an easy-to-use instrument for monitoring people's health status. Numerous researchers in many countries have done a study on handgrip disease or demographic data. This study focused on classifying aged groups referring to handgrip value using machine learning. A total of fifty-four participants had involved in this study, ages ranging from 24 years to 57 years old. Digital Pinch Grip Analyzer had been used to measure the handgrip measurement three times to get more accurate results. The result is then recorded by Clinical Analysis Software (CAS) that is built into the analyzer. An independent t-test is used to investigate the significant factor for age group classification. The data were then classified using machine learning analysis which are Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes. The overall dataset shows that the Support Vector Machine is the most suitable classification technique with average accuracy between 5 groups of age is 98%, specificity of 0.79, the sensitivity of 0.9814 and 0.0185 of mean absolute error. SVM also give the lowest mean absolute error compared to RF and Naïve Bayes. This study is consistent with the previous work that there is a relationship between handgrip and age.

Keywords: Handgrip measurement, machine learning technique, age classification

1. Introduction

Handgrip strength appears to be an attractive, easy-to-use instrument for monitoring health status among adults or the elderly [1]-[10]. It is a simple and fast clinical measurement that has emerged as a proxy assessment of overall muscular strength. HGS also a general indicator of muscle strength linked with premature mortality. Using a handgrip dynamometer, one can measure how much static force their hand can squeeze under standard conditions. Newtons and kilograms are the most prevalent units of measurement for the force. The American Society for Surgery of the Hand and the American Society of Hand Therapists have standardized the posture, instruction, and computation of grip strength of patients during measurements, as there are various techniques [11].

Several studies have been done between handgrip and age in other countries. In Brazil, a group of researchers investigated the effect of gender and age on handgrip strength. According to them, both men and women experienced handgrip declines as they got older. The handgrip strength of men in this demographic peaks around 30 and subsequently declines with age [12]. Werle et al. measured grip and pinch strength in a typical Swiss population and came up with age and gender-specific reference values. In men, handgrip peaks between 35 and 39, while for women, handgrip peaks between 40 and 44 and then decline after that point [13].

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Saudi Arabian researchers developed normative values of HGS based on gender and age [14]. HGS was found to be adversely correlated with age for both men and women. However, because the sample was restricted to senior citizens in the Riyadh area, it cannot be applied to the entire Saudi population. They indicated that further research is needed in Saudi Arabia to verify the current findings. Next, a study on the Greek adult population concludes with a negative correlation between age and handgrip strength. According to the researchers, people's HGS declines after age 50, forming a curvilinear link between age and hand strength [15].

In Malaysia, other researchers conducted a study among the elderly to assess the association between HGS and non-communicable diseases (NCDs) and the related risk factors [16]. This study revealed that the amount of HGS levels fell dramatically as a person grew older and was higher in males. A study on handgrip strength among Malaysian population aged 18 to 65 years old was done by T. Kamarul suggested that there should be at least three measurements taken with a standard dynamometer to increase the validity and reliability of HGS assessments [17].

Toyin Ajisafe utilized six methods of machine learning algorithm, which are coarse tree, quadratic discriminant, logistic regression, kernel naïve Bayes, quadratic SVM, and weighted KNN, to see if it was possible to use anthropometrics, demographics, and handgrip strength data to build optimal Cardiometabolic (CMB) risk classifiers [18]. The researcher found that the coarse tree outperformed the other machine learning method with an accuracy of 85% in classified CMB risk data. Despite the successful result of this study, the author listed some limitations, including fewer amounts of data.

Next, a group of researchers compared two types of machine learning algorithms, KNN and ANN, to predict the high and low-performance archers from a set of selected fitness and motor skill parameters. They found that ANN is better than KNN since the accuracy of ANN is 92% while the accuracy of KNN is 80% [19]. Future research should provide insightful information about other related performance parameters that influence performance in sports using non-conventional classification techniques. Woo Chaw Seng and Mahsa Chitsaz used Adaptive Neuro-fuzzy Inference System (ANFIS) in a novel technique of handgrip tension measurements [20]. The neuro-fuzzy analysis identifies systems, interprets fuzzy models, and enables neural networks to learn. The study produces a good accuracy result using neuro-fuzzy, which is 90%. The author suggested that future work should focus on determining the optimal method for finding the correct number of membership functions for each fuzzy rule.

Kabeshova et al. identified the efficiency of 3 artificial neural networks (ANNs: multilayer perceptron [MLP], modified MLP, and neuroevolution of augmenting topologies [NEAT]) for the classification of recurrent fallers and nonrecurrent fallers using a set of clinical characteristics corresponding to risk factors of falls measured among community-dwelling older adult [21]. Between the three ANNs, NEAT was discovered as the most efficient method for identifying recurrent fallers in older community dwellers compared to MLP and modified MLP with an accuracy of 88.39%. Nevertheless, the authors suggested comparing the efficiency of ANNs with classical linear statistical approaches using data from prospective cohort studies in future works.

This study focused on classifying the aged group by referring to handgrip data. Both handgrip strength measurements were measured at Kampung Sungai Tiang and Universiti Teknologi Malaysia (UTM) Kuala Lumpur. The next part will be discussed research methods, including sampling data, handgrip data collection procedure, statistical analysis, data classification, and finally, data validation. Then the result is tabulated in section 3 for both statistical and machine learning analysis

2. Research Methodology

There are two sets of data from the Orang Asli community (Kampung Sungai Tiang, Royal Belum Forest) and the UTM staff community (Universiti Teknologi Malaysia Kuala Lumpur). Analysis of data includes age and handgrip reading from both groups. This paper is extended from [22], which discovered handgrips among the Orang Asli community and resulted in the handgrip value being similar between two different groups of malnutrition. Thus, this study performed critical analysis on the handgrip based on age group, including some analysis using machine learning methods.

2.1 Sampling

Fifty-four participants were involved in this study, whose age ranged from 24 to 57 years old. The subjects included twenty-two participants from the Orang Asli community and thirty-two from the UTM staff community. The total male and female participants involved are thirty-one and twenty-three, respectively. This study excluded the subjects who had surgery related to the arm within the last three months, had issues with upper limb injury, and with difficulty gripping their hand.

Before data collection, the head of the community, locally known as Tok Batin, was verbally informed about the study and obtained verbal informed consent from him. All subjects were briefed on the purpose of the study, and informed consent were obtained from them before any measurements were taken. A structured questionnaire was prepared in Bahasa Malaysia tailored explicitly to the Orang Asli community to ensure effective data collection. All subjects were interviewer-administered to provide information on demographic data such as gender, ethnicity, age, weight, health status, and daily dairy intake. On the other hand, the subjects from the UTM staff community are self-administered to answer the demographic questions.

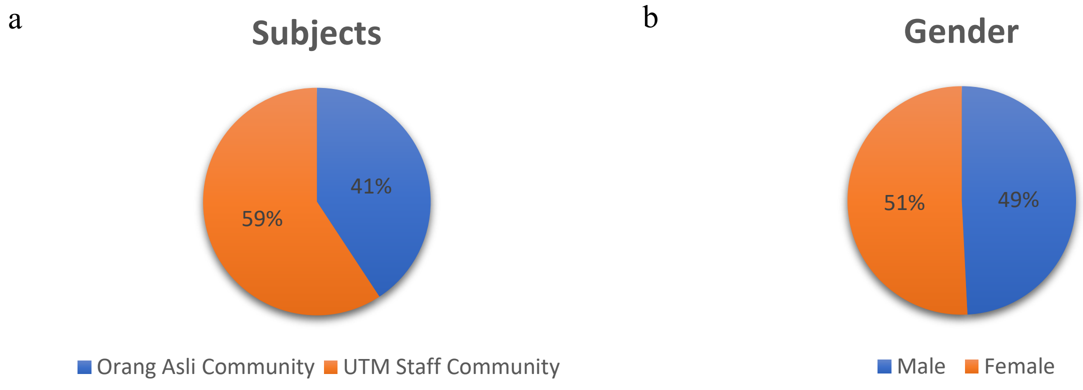

Fig. 1 - Pie chart of the dataset (a) by subjects; (b) by gender

2.2 Handgrip Data Collection

An MIE Digital Pinch/Grip Analyzer was used for handgrip strength measurement in both locations. This handgrip analyzer is a precision instrument to ensure maximum accuracy and resolution [23]. Handgrip data measured in kilogram units are recorded by CAS Software that is built into the analyzer. The software then does the relevant analysis to produce the maximum value of grip force.

The subjects will first be briefed and demonstrated by the researchers. The setting for the data collection procedure and the entire procedure in the standing position is shown in Fig. 2. The handle width is set consistently for all subjects. The subjects must hold the grip analyzer handles 2cm below the red indicator line without assistance. They must grip the Digital Pinch/Grip Analyzer for 5 seconds to assess muscle strength and then rest for 15 seconds. They will follow the sign shown in the software interface as in Fig. 3. The procedure will be repeated three times, with the mean value recorded each time. Subjects are advised to grip their maximum as quickly as possible to reduce fatigue. The handgrip value will be recorded, and the result will be displayed in CAS software, as shown in Fig. 4.

a b

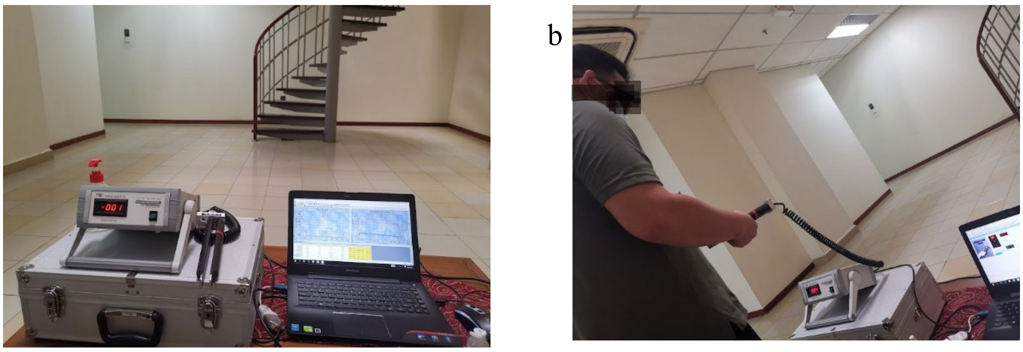

Fig. 2 - Handgrip measurement (a) data collection setting; (b) standing position

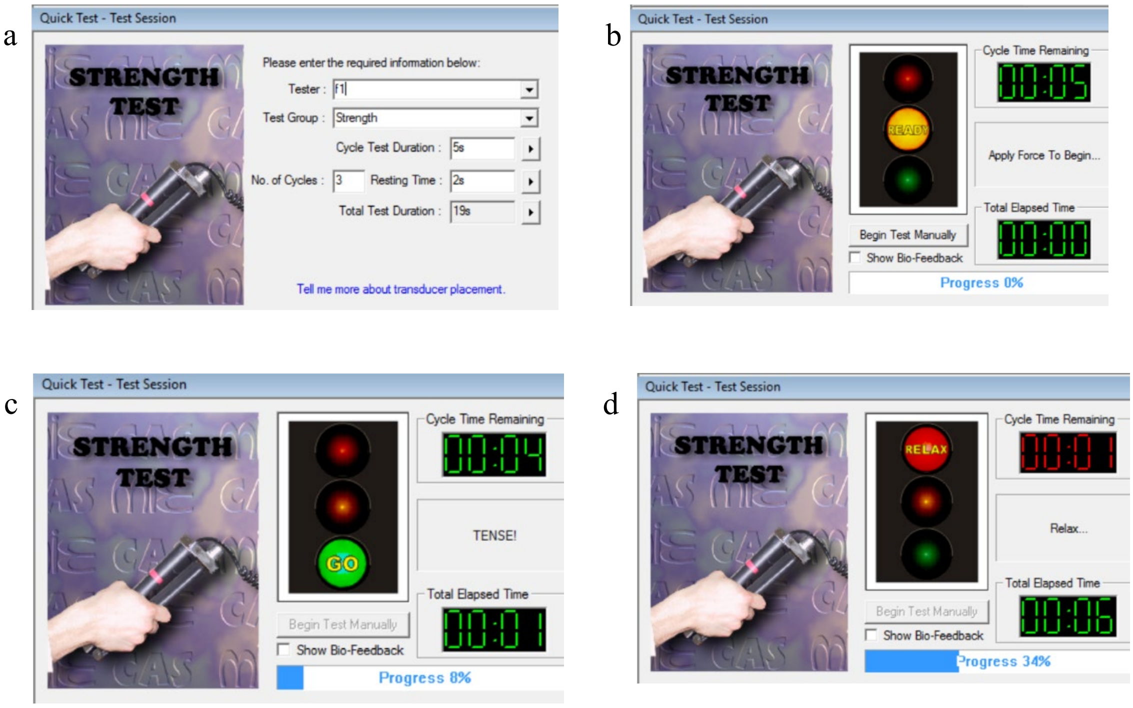

Fig. 3 - CAS software interface (a) data entry; (b) ‘ready’ sign; (c) ‘go’ sign; (d) ‘relax’ sign

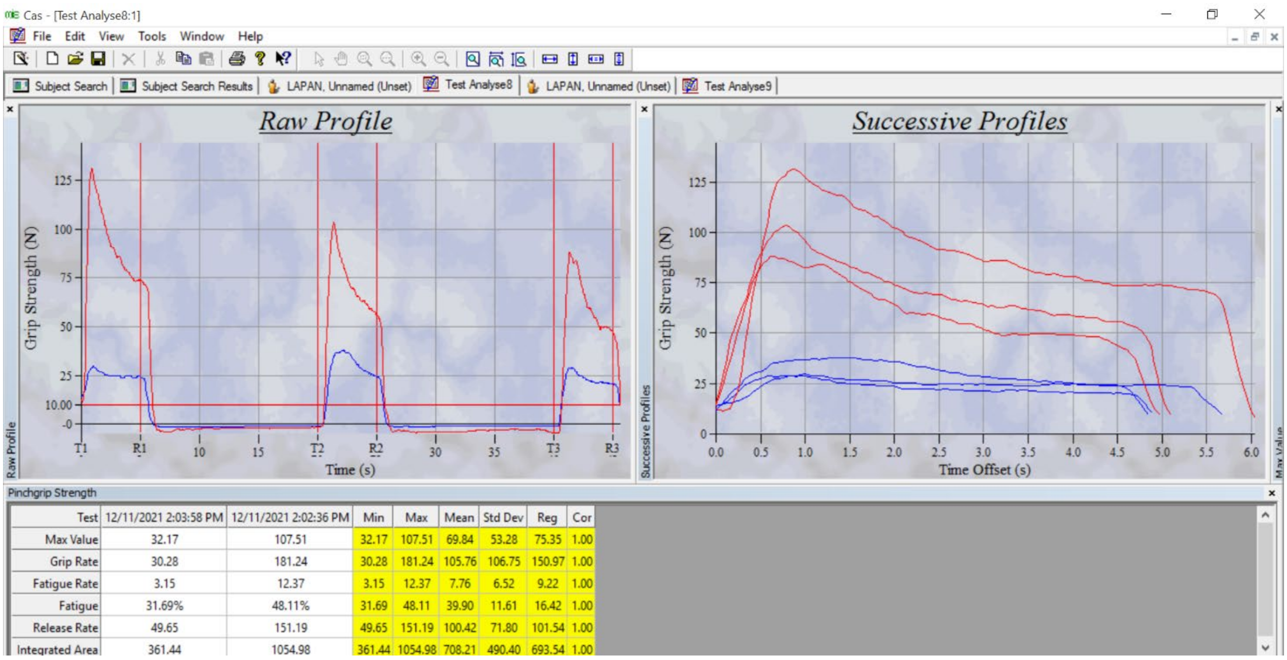

Fig. 4 - Result for handgrip and hand pinch in standing position

2.3 Statistical Analysis

All statistical analysis was performed using SPSS software version 26. The attributes involved are age, gender, weight, hand dominance, three handgrips reading, max value of handgrip, three hand pinch readings, and max value of hand pinch. All data has been divided into two age groups: below 35 years old and above 35 years old. An independent t-test was used to analyze the significant factor for the age group classification. The significance level of 95% indicates significance in all the statistical analyses.

2.4 Data Classification

The Waikato Environment for Knowledge Analysis (WEKA) dataset was classified based on age intervals [24]. A group of subjects in the dataset was discretized to create a smaller group number of age intervals. Discretization converts the attributes in the data into continuous data with the least amount of data loss [25]. This study has five groups of age intervals: i) 24 - 30, ii) 31 - 37, iii) 38 - 43, iv) 44 - 50, and v) 51 and above. From one attribute of age in nominal, the data is converted to binary so that the age data is distributed into five attributes. Either one attribute is set as a class. Then, the dataset was normalized for the numerical attributes to nominal attributes so that the data could be processed quickly and without duplication before the classification process could start. The attributes uses for classification is shown in Table 1.

Table 1 - Description of attributes

Attribute	Description
Age	Age of the subject
Gender	The subject can be either male or female
Grip_R1	First reading of handgrip measurement
Grip_R2	Second reading of handgrip measurement
Grip_R3	Third reading of handgrip measurement
Max_Grip	Average of three handgrip measurement

This study employs some machine learning techniques, which are support vector machine (SVM), random forest (RF), and Naïve Bayes (NB). These techniques were utilized to classify the dataset based on the age intervals to achieve data accuracy, sensitivity, specificity, and mean absolute error. Supervised classification and regression can be performed using SVM by mapping the data between input vectors and a large viewpoint space [26]. SVM works well with small datasets and a reliable classification system. Linear SVM is used to classify the data points using a single straight line known as a decision boundary. It maximizes the marginal distance between the nearest points and the output hyperplane. The hyperplane equation is the primary separator line, formulated as in Eq. 1,

$$\boldsymbol{d_H(\phi(x_0)) = \frac{|w^T(\phi(x_0))+b|}{\|w\|_2}} \tag{1}$$

Where $\boldsymbol{w^T(\phi(x_0)) + b = 0}$ is the distance of the hyperplane equation, and $\|\boldsymbol{w}\|_2$ is the Euclidean norm for the length of *w*. A positive group point is substituted into the hyperplane equation for generating predictions on binary data classified as positive or negative. If the forecast is correct, the total of the predicted and actual labels would be more than 0; otherwise, it would be less than zero, as shown in Eq. 2.

$$\boldsymbol{y_n[w^T(\phi(x_0)) + b] = \begin{cases} \geq 0 \; if \; correct \\ < 0 \; if \; incorrect \end{cases}} \tag{2}$$

In machine learning, the RF is used to do classification and regression. It utilizes ensemble learning, which involves integrating several classifiers to tackle complex issues and enhance the model's performance [27]. Generally, a class prediction is performed by each tree, and the class with the majority of votes is the predicted final output. The RF prevents overfitting of the data and trains the data quickly. The Gini index can be computed to determine which branch is more likely to occur on a node. It is formulated as in Eq. 3:

$$\boldsymbol{Gini = 1 - \sum_{i=1}^{C}(p_i)^2} \tag{3}$$

Where $\boldsymbol{p_i}$ is the relative frequency of the class in the dataset, and *c* is the number of classes. Other than Gini, Entropy is used to determine the nodes' branches in decision trees mathematically. The entropy is calculated as in Eq. 4,

$$\boldsymbol{Entropy = \sum_{i=1}^{C} -p_i * \log_2(p_i)} \tag{4}$$

The Naïve Bayes, also known as numeric estimator precision values, is a supervised machine learning method that uses a basic probability distribution. Compared to the SVM technique, Naïve Bayes requires less time to train due to its emphasis on the expectations of freedom. The precision values of Naïve Bayes are determined on the training data. It is computed as in Eq. 5:

$$\boldsymbol{P(A|B) = P(B|A) \times \frac{P(A)}{P(B)}} \tag{5}$$

Where $\boldsymbol{P(A|B)}$ is the posterior probability, and $\boldsymbol{P(A)}$ is the prior probability representing the likelihood that the event will occur.

2.5 Data Validation

10-fold cross-validation is used to validate the classification of the training set [28], [29]. Repeating the classification procedure with 10-folds helps determine the accuracy of a classifier. The total number of correctly classified from 10 iterations is divided by the total number of groups in the initial data to estimate the accuracy. Practically, 90% of data is used for training, while 10% of data is utilized for testing. This shows that 47 data is used for training and 5 data used for testing. The process is then repeated ten times. Lastly, the mean ten times validation result is used as the final rate estimation.

The performance of classification models is measured in terms of the test records being correctly and incorrectly classified, true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The TP refers to positive attributes that the classifier correctly classified, TN refers to negative attributes that the classifier correctly classified, FP refers to negative attributes that were incorrectly classified, and FN refers to positive attributes that the classifier incorrectly classified.

3. Result and Discussion

Table 2 displays the descriptive statistics for all data. The skewness and kurtosis values of data distribution are referred to as skewness and kurtosis values, and Table 2 shows that the data is normally distributed. The range of normal distribution is between -1 and +1 for skewness and kurtosis.

Table 3 shows the weight, handgrip, and hand pinch data for age groups '35 and below' and 'above 35'. Table 3 indicates a statistically significant difference in all readings for handgrips between people aged 24 to 35 years and above 35 years, with a p-value<0.05. Nevertheless, both groups have similar readings for hand pinch and weight. From the finding, this study aligns with previous studies, which stated that handgrip is a peak at 35 to 39 years before declining after that [13]. Furthermore, Table 4 compares handgrip value among males and females. It shows that male is stronger than female, with a handgrip of 28kg compared to 16kg.

Table 2 - Descriptive statistics for all data

Characteristic	Mean	SD	Skewness	Kurtosis
Age	36.85	8.116	0.350	-0.823
Weight	65.11	16.816	0.475	-0.496
Grip_R1	23.23	11.190	0.710	-0.434
Grip_R2	22.74	11.362	0.813	-0.256
Grip_R3	22.16	11.402	0.734	-0.491
Max_Grip	22.71	11.214	0.752	-0.416
Pinch_R1	7.00	2.242	0.171	-0.580
Pinch_R2	6.68	2.189	0.092	-0.446
Pinch_R3	6.65	2.235	0.124	-0.257
Max_Pinch	6.78	2.164	0.165	-0.452

Table 3 - Comparison analysis for two age groups

Characteristic	35 and below (N=25)		Above 35 (N=29)		p-value
	Mean	SD	Mean	SD	
Weight	63.74	18.108	66.29	15.844	0.582
Grip_R1	27.20	11.965	19.82	9.394	0.014
Grip_R2	26.61	12.310	19.41	9.466	0.019
Grip_R3	26.51	12.564	18.40	8.905	0.010
Max_Grip	26.77	12.123	19.21	9.201	0.014
Pinch_R1	7.22	2.411	6.81	2.111	0.515
Pinch_R2	7.12	2.394	6.29	1.958	0.171
Pinch_R3	7.10	2.593	6.27	1.835	0.179
Max_Pinch	7.14	2.409	6.46	1.914	0.251

Table 4 - Handgrip value based on gender

Gender	Handgrip	
	Mean	SD
Male	28.23761	11.3324
Female	16.53936	5.903712

Since the statistical analysis had analyzed that handgrip reading has a significant difference with age, the study proceeded with classifying the age group using machine learning. The classification result for the age group is shown in Table 5, Table 6, and Table 7. The results indicate age group '51 and above' has a similar classification accuracy of 96.3% for all algorithms, but the specificity is 0 since there is no TP data in that group. It is because the data in the group have minimal value and cannot be analyzed.

In Table 5, the age group is classified using SVM, which results in more than 96% of accuracy. Age groups 31-37 and 44-50 give 100% accuracy, 1.0 specificity, and 1.0 sensitivity. However, the accuracy of the 24-30 age group is 96%, with 0.967 specificities and 0.963 sensitivity. Group 38-43 give 98% accuracy, 0.983 specificities and 0.981 sensitivity. Table 6 shows the classification result using RF with an accuracy above 80%. Both the 31-37 and 44-50 age groups give the same accuracy, which is 90% and 0.907 sensitivity. Yet, the absolute error gives different values of 0.2072 and 0.1987, respectively.

Meanwhile, for Naïve Bayes in Table 7, the accuracy is the lowest in the age group 24-31 at 77%, 0.769 specificities, and 0.778 sensitivity. The lowest mean absolute error is 0 for age groups 31-37 and 44-50 using SVM compared to Naïve Bayes at 0.0659 and RF 0.0724, respectively. The average accuracy using SVM is 98%, using RF is 88%, and the average accuracy of Naïve Bayes is 87%. This result shows that SVM outperformed other algorithms in classifying age groups based on handgrip value.

Table 5 - Classification result using Support Vector Machine

Age Group	Accuracy (%)	Specificity	Sensitivity	Mean absolute error
24-30	96.2963	0.967	0.963	0.037
31-37	100	1.000	1.000	0
38-43	98.1481	0.983	0.981	0.0185
44-50	100	1.000	1.000	0
51 and above	96.2963	0	0.963	0.037
AVERAGE	98.14814	0.79	0.9814	0.0185

Table 6 - Classification result using Random Forest

Age Group	Accuracy (%)	Specificity	Sensitivity	Mean absolute error
24-30	81.4815	0.811	0.815	0.2372
31-37	90.7407	0.907	0.907	0.2072
38-43	85.1852	0.843	0.852	0.2222
44-50	90.7407	0.904	0.907	0.1987
51 and above	96.2963	0	0.963	0.0724
AVERAGE	88.88888	0.693	0.8888	0.18754

Table 7 - Classification result using Naïve Bayes

Age Group	Accuracy (%)	Specificity	Sensitivity	Mean absolute error
24-30	77.7778	0.769	0.778	0.2071
31-37	90.7407	0.906	0.907	0.1175
38-43	92.5926	0.926	0.926	0.1088
44-50	81.4815	0.766	0.815	0.1372
51 and above	96.2963	0	0.963	0.0659
AVERAGE	87.77778	0.6734	0.8778	0.1273

4. Conclusion

This paper discussed age group classification based on handgrip and hand pinch analysis. Fifty-four subjects were involved in this study, ranging from 24 to 57 years old. The handgrip and hand pinch readings are analyzed using statistical analysis of an independent t-test to observe their relationship with age. But only handgrip data have a significant difference with age. Then the datasets were classified using SVM, Random Forest, and Naïve Bayes. The accuracy is above 77%, which means a strong relationship between handgrip and age since the algorithm can classify with good accuracy. Based on the overall dataset, the finding shows that SVM is the most suitable classification technique because the error rate for all groups is the lowest compared to RF and Naïve Bayes. This study is consistent with the previous work that there is a relationship between handgrip and age.

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