THIRD MOLAR MATURITY INDEX IN INDONESIAN JUVENILES: COMPARING LINEAR AND POLYNOMIAL KERNEL PERFORMANCE IN SUPPORT VECTOR REGRESSION FOR DENTAL AGE ESTIMATION

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Abstract: Dental age estimation is a branch of forensic odontology that plays a pivotal role in identifying, examining, or determining the legal status of the living and the dead. This research explores the capability of support vector regression to estimate chronological age from the third molar maturity index (I_{3M}) in Indonesian Juveniles and compares the linear and kernel performance. Two hundred and twenty-two orthopantomography were measured using I_{3M} in the lower left third molar and processed using R Studio with Caret extension. The analysis was separated into two groups, group 1 using only I_{3M} as a predictor, and group 2 using both I_{3M} and sex. Both groups were analyzed using SVR with the linear and polynomial kernel. The result suggests that using polynomial kernel SVR in group 1 produces the best results, with *an R^2* value of 0.64, *RMSE* of 1.588 years, and MAE of 1.25 years using degree = 3, c = 0.25. However, the addition of a sex predictor in the model reduces its accuracy when using the polynomial kernel.

1. INTRODUCTION

Age is essential information for an individual. Through the knowledge of age, one could determine important landmarks throughout their life, whether in life or death (Duangto et al., 2017). For example, when they are reaching the legal state of adulthood to receive criminal responsibility, pension, or to determine the threshold to join in an age-restricted tournament in sport events (Bjork & Kvaal, 2018). In death, age serves as a guide for creating a victim profile, closing the gap in searching for their identity (Pretty & Sweet, 2001).

The importance of age has become a critical matter in forensics, especially in forensic odontology. A tooth had known as a reliable parameter in estimating an individual dental age, as it has a strong correlation with chronological age (Macha et al., 2017), and it can endure extreme hazards (e.g. high temperature) (Cardoza, 2004). Therefore, the keyword "*estimate*" creates an opportunity to determine the most accurate dental age estimation in various research approaches. By utilizing the various changes in the tooth, whether a growth progression or regression, forensic odontologists were able to establish numerous methods to estimate an individual's age (De Tobel et al., 2017; Kvaal & Solheim, 1994).

In 2008, Cameriere et al. proposed a new metric method for dental age estimation in juveniles called the third molar maturity index (I_{3M}) (Cameriere et al., 2008). This method utilizes an orthopantomogram (OPG) and measures the lower left third molar (Federation Dentaire Internationale (FDI) numbering 38) open apices, then dividing it by its tooth length, effectively eliminating the differences in magnification and angulation in the OPG (Cameriere et al., 2006). The I_{3M} method was already tested in the Indonesian population, and it was found that the development of Indonesian juveniles was slower than in other countries (Angelakopoulos et al., 2018; Balla, Banda, et al., 2019). Hence, a specific dental age estimation equation for Indonesian juveniles' I_{3M} needs to be generated.

Linear or polynomial regression was commonly used in dental age estimation (Balla, Lingam, et al., 2019). Fortunately, the accessibility of supervised machine learning creates a new opportunity to integrate it into the dental age estimation method. One of the techniques used to handle regression problems is Support Vector Regression (SVR). SVR works by developing an optimization problem to analyze a regression function from the input predictor variable to output observed response values (Zhang & O'Donnell, 2020). SVR is an extension of Support Vector Machine (SVM) classification, which is commonly used to handle classification problems (i.e., sex determination, legal age) (Vapnik, 2013).

The difference between SVM and SVR is in hyperplane usage. SVM utilized the hyperplane to separate two distinct variables. On the other hand, SVR attempt to fit the hyperplane and decision boundary with the maximum number of data points (Gunn, 1998). Furthermore, SVR can handle a nonlinear regression problem using a kernel by transferring the original data into a kernel space where the data can be linearized (Ben-Hur et al., 2008). Based on this background, this paper aimed to compare the performance of R^2, Root Mean Squared Error (*RMSE*), and Mean Absolute Error (MAE) of SVR with the linear and polynomial kernel to estimate the dental age of Indonesian juveniles with I_{3M} method. Finally, to evaluate the model, we use a K-fold Cross-Validation (KCV) system.

2. LITERATURE REVIEW
2.1. Third Molar Maturity Index

I_{3M} is a metric measurement method proposed by Cameriere et al. (2008) for the lower third molar by extending the measurement used in the permanent developing tooth (Cameriere et al., 2006; Cameriere et al., 2008). This method differentiates the lower third molar measurement method into three different phases. The first phase is the crown phase; where there is no bifurcation (or root separation) seen, the length of the root (A_8) then will be divided solely by the tooth height (L).

$$I_{3M} = \frac{A_8}{L}$$
(1)

The second phase is the bifurcation phase, where the lower third molar already developed both of its roots. Hence, the sum of both roots ($A_{81} + A_{82}$) will be divided by the tooth height (L). Finally, the third phase is when the root of the third molar is closed, this will be counted as $I_{3M} = 0$ (Figure 1).
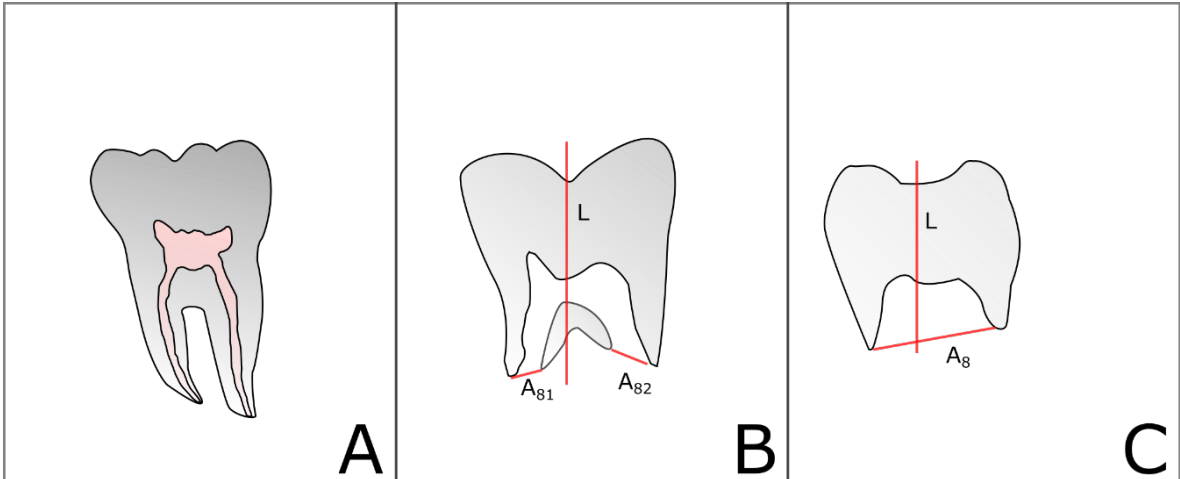
$$I_{3M} = \frac{A_{81} + A_{82}}{L}$$
(2)

Figure 1. Illustration of Third Molar Maturity Index. 'A' represents a closed root of the third molar, $1_{3M} = 0$. 'B' represents the bifurcation phase with two root measurements $\left(I_{3M} = \frac{A_{81}+A_{82}}{L}\right)$. 'C' Represents the crown phase with no bifurcation $\left(I_{3M} = \frac{A_8}{L}\right)$.

2.2. Support Vector Regression

As stated above, the goal of SVR is to create a model trained to estimate a function between a set of constraints to find a hyperplane that can approximate all the input data points (Smola, 1996). This was done by introducing an ε-insensitive loss function to process a hyperplane. Thus, the predicted response values of the training samples (e.g., estimated dental age) have at most an ε deviation from the actual response values (e.g., chronological age).
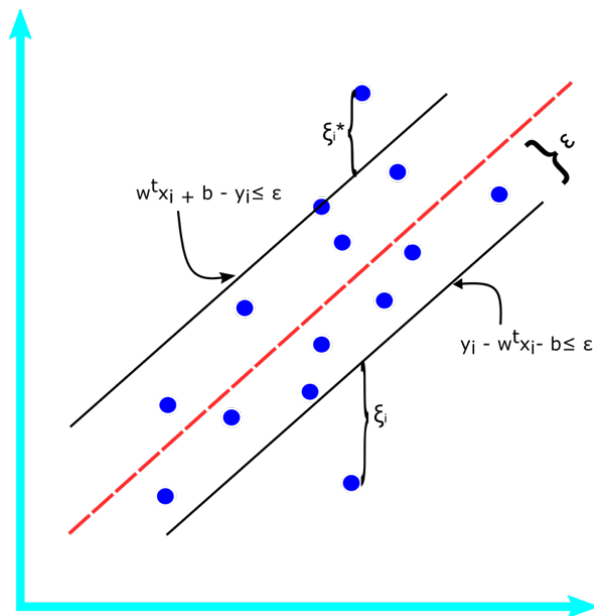

Figure 2. Illustration on Support Vector Regression with assigned hyperplane (red) and ε-insensitive band (black).

The hyperplane with ε defines an ε-insensitive band for calculating constraints in the regression model. This model can be optimized by minimizing the ε-insensitive band as

narrow as possible while containing most training samples. A few support vectors signify the hyperplane. This SVR training process will generate a regression model to predict a new sample (Vapnik, 2013). To explain the SVR fully, we start with a simple case of a linear SVR model. Suppose we have training data

$$D = \{(x_1, y_1), \ldots, (x_l, y_l)\} \tag{3}$$

where x_l is the input data and y_l is the target output. The linear function of f may take the form

$$y = f = w, x + b = w^T x + b \tag{4}$$

where w, x denotes the coordinates or dot product of input data x and the weight vector w. The function of f approximation is performed by finding an ε-insensitive band as flat as possible, i.e., seeking a small w. This approximation can be made by regulating the norm of w as

$$min_w \frac{1}{2} \|w^2\|,$$

$$\text{subject to} \begin{cases} y_i - w^T x_i - b \leq \varepsilon \\ w^T x_i + b - y_i \leq \varepsilon \end{cases} \tag{5}$$

The ε-insensitive loss function was the essence of SVR, and it is done through chastening predictions that are farther from the ε boundaries from the wanted output. The value of ε plays an essential role in the flatness of the band, whilst the small ε value creates a narrow band and low tolerance of errors, and a large ε value creates a wideband and high tolerance of error (Smola, 1996). Several ε-insensitive loss functions are shown below for linear and quadratic functions.

$$L(y, f(x)) = \begin{cases} 0 & if \ |y - f(x)| \leq \varepsilon \\ |y - f(x)| - \varepsilon & otherwise \end{cases} \tag{6}$$

$$L(y, f(x)) = \begin{cases} 0 & if \ |y - f(x)| \leq \varepsilon \\ (|y - f(x)| - \varepsilon)^2 & otherwise \end{cases} \tag{7}$$

The optimization in Eq. (5) is doable if a function f can approximate all data points (x_i, y_i) with an ε precision. However, this does not translate well in real-life applications, as there are outlier data points. Hence, the model needs to counterbalance this with prediction errors by introducing slack variables (Tang et al., 2015). Slack variables ξ and ξ^* can be added to Eq. (5) to compensate for outliers. These variables determine how many data points can be compensated outside the ε-insensitive band. The optimization problem in Eq. (5) can be adapted with additional parameters

$$min_w \frac{1}{2} \|w^2\| + C \sum_{i=1}^{l} (\xi_i + \xi_i^*)$$

$$\text{subject to} \begin{cases} y_i - w^T x_i - b \leq \varepsilon + \xi_i \\ w^T x_i + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i + \xi_i^* \geq 0 \end{cases} \tag{8}$$

where $C > 0$ is a parameter regularization that determines the flatness of function f and prediction error trade-off. C value affects the weight of prediction errors and flatness; a considerable C value assigns more weight to error prediction minimization, while a small C

gives more weight to flatness minimization (Zhang & O'Donnell, 2020). The ε-insensitive loss function can be determined as follows:

$$L\big(y, f(x)\big) \;=\; L(\xi) \;=\; \begin{cases} 0 & if \; |\xi| \le \varepsilon \\ |\xi| \,-\, \varepsilon & otherwise \end{cases} \tag{8}$$

To allow SVR to compute nonlinear data, a kernel function can transform the original input into a higher-dimensional space called a feature space. This kernel trick is famous for its performance in learning nonlinear decision boundaries through $\boldsymbol{\varphi}$ (Ben-Hur et al., 2008).

$$\varphi : \; x \;\to\; \varphi(x) \tag{9}$$

Then, the optimization problem of $\boldsymbol{f(x)}$ in terms of $\boldsymbol{\varphi(x)}$ can be written as follows:

$$y \;=\; f(x) \;=\; \langle w, \varphi(x)\rangle \;+\; b \;=\; w^T \varphi(x) \;+\; b \tag{10}$$

In this research, we will use two types of kernels with $\boldsymbol{K(x,y)}$ corresponding to a feature space's inner product based on $\boldsymbol{\varphi}$ mapping, linear and polynomial. The linear kernel is the most straightforward function presented in Eq. 12 with a constant term (c). On the other hand, in the polynomial kernel, data is suited by adding a flexible polynomial degree (d) from its linear kernel counterpart, forming a nonlinear equation using a certain chosen degree (Eq. (12)).

$$\varphi(x) \;=\; K(x,y) \;=\; x^T y \;+\; c \tag{11}$$

$$\varphi(x) \;=\; K(x,y) \;=\; \big((x^T y) \;+\; c\,\big)^d \tag{12}$$

2.3 K-Fold Cross-Validation

KCV is a practical approach to measuring model reliability and error estimation (Anguita et al., 2012). KCV works by randomly dividing the data into k disjoint folds with approximately the same number of instances. Consequently, every fold, in turn, acts for testing the model generated from other $k-1$ folds (Wong & Yeh, 2020).

The rule-of-thumb methods refer to many k (5,10, and 20) to exploit a more significant number of patterns for training purposes (Hsu et al., 2003). Others suggested adding a repeated measure; the data may obtain reliable accuracy estimates for statistical comparison (i.e., performing 10-fold CV 10 times) (Bouckaert, 2003).

3. MATERIAL AND METHOD

Two hundred and twenty-two OPG images comprising 73 males and 149 females were collected from Pramita Laboratory, Semarang, Indonesia, with ages ranging between 15 to 23.99 years old. The sample was selected based on the availability and clarity of 38 without any recorded caries, dental treatment, or any form of systemic disease that may hinder the growth of 38. The anonymity of the sample was kept, and necessary ethical approval was obtained from the local institute committee. Furthermore, I_{3M} was the first predictor variable (x_1) and gender as the second predictor (x_2), whilst the known age was the outcome variable. The analysis was separated into two distinct groups, Group 1 using only x_1 and group 2 using both x_1 and x_2.

To perform the measurement, OPG was exported to a *.jpeg* format and measured in Adobe Photoshop CC 2020. Minimal enhancement such as contrast, or brightness adjustment was allowed. The measurement was performed in conjunction with Cameriere et

al. (2008) I_{3M} technique. The results from the previous segment were then collated into Microsoft Excel 365 and processed using R Studio with caret extension (Kuhn, 2008; Team, 2020).

Data were analyzed using caret with the selection of linear and polynomial SVR kernels. First, the *TrainControl* value was assigned to a KCV method, with 5-fold and five repetitions. Secondly, the data was transferred into *train* function with *svmLinear* and *svmPoly*, which was assigned to a regression function with *tuneLength* set to 4. Kernel polynomial function parameter (i.e., degree and c) then was assigned automatically by the program by KCV parameter while measuring the highest R^2 and lowest *RMSE* and Mean Average Error.

4. RESULTS AND DISCUSSION

The descriptive statistics of the sample are presented in Table 1. I_{3M} had a medium negative correlation with age (-0.65, $p<0.05$.) The first $I_{3M} = 0$ was observed in 21.5 and 20.3 years old in male and female, respectively.

Table 1. Descriptive Statistics of the Collected Sample.

Gender	Total	Mean age (years old)	Mean I_{3M}
Male	73	18.6 ± 2.57	0.188 ± 0.255
Female	149	19.5 ± 2.57	0.21 ± 0.196
Total	222	19.2 ± 2.6	0.202 ± 0.237

Linear basis kernel analysis of Group 1 resulted from the model's R^2 value of 0.430 with an RMSE of 1.992 years and MAE of 1.716 years old when c is held constant at 1. Further adjusting the c value, we observe that the model did not improve significantly over the previous model ($c = 0.1$, $R^2 = 0.439$, RMSE = 1.991, and MAE = 1.712). By adding the x_2 predictor in group 2, the model achieved an R^2 value of 0.444 with RMSE of 1.953 years old and MAE of 1.6 years old when c is held constant at 1. When the c value was adjusted, the model improved slightly with the choice of $c = 0.1$ ($R^2 = 0.45$, RMSE = 1.946, MAE = 1.59).

In the nonlinear method using the polynomial kernel, Group 1 attained an R^2 value of 0.64, the lowest RMSE value of 1.588 years, and MAE of 1.25 years using degree = 3, $c = 0.25$. Furthermore, by adding the x_2 predictor in Group 2, the model reached an R^2 value of 0.63 with an RMSE value of 1.596 years and MAE of 1.30 years using degree = 3, $c = 2$. Unlike the linear counterpart, the addition of sex information in the polynomial kernel model seems to reduce the accuracy of chronological age prediction. Additionally, cost and degree simulations are displayed in Figure 3.
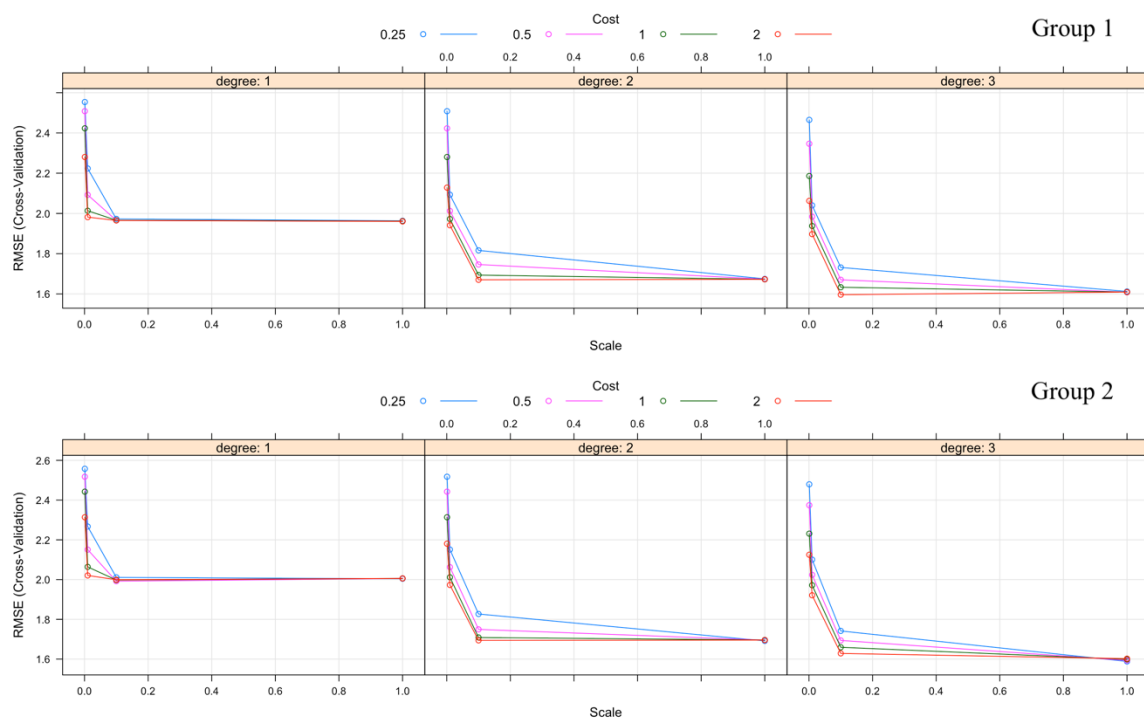
Figure 3. Cost and degree simulations were demonstrated in Group 1 and 2 using a polynomial kernel.

The lowest RMSE and MAE were obtained from the tested models with a third-degree polynomial kernel. It showed that the growth of the 38 is not linearly correlated with chronological age. All the chosen costs and degrees that had been tested in the regression model were based on the lowest cross-validated RMSE, with both polynomial kernels achieving the lowest RMSE using the third degree and 0.25 cost value in group 1. Although using a third-degree regression to estimate age in dental has been explored, it is reported that the use of a polynomial regression should depend on the independent variable (Chaillet et al., 2004; De Luca et al., 2016). Furthermore, by adding sex as a predictor variable, the RMSE was decreased by a small amount (0.01). Hence, this model should be used without considering the sex information.

Age estimation of a living individual is essential to determine criminal investigation or civil administration (Bjork & Kvaal, 2018). Examination of bone age was the most widely used method. However, dental age estimation was performed as well as the skeletal age estimation. The challenge for forensic practice is to develop and assess the high accuracy of population-specific methods in estimating age.

The utilization of the third molar in the field of age estimation had met with various intricacies. First, the third molar varied in its morphological development, creating variations in size, shape, and root number (Nelson & Ash, 2010). This morphological variation is in line with human evolutions. Hence, in specific populations, the case of third molar agenesis becoming more common (Carter & Worthington, 2015). Furthermore, the presence of the third molar is often correlated with several pathological events, which made third molar extraction more common (Altan & Akbulut, 2019). Finally, the third molar various position in the human jaw made it difficult to observe in 2D radiographs (Rai et al., 2010). However,

regardless of all of the difficulties, the third molar is still the most reliable dental age-related variable in the juvenile age group (Cameriere et al., 2004).

Age estimation methods based on third molar development had been evaluated in the Indonesian population (Saputri, 2020). However, for I$_{3M}$ methods by Cameriere et al. specific model has not yet been analyzed as the I3M method is more commonly used to assess legal age by using a specific cut-off value of <0.08, evaluated for applicability and reliability in different populations (Gomez Jimenez et al., 2019; Rozylo-Kalinowska et al., 2018).

Prabowo et al. showed significant differences between the I$_{3M}$ index between individuals above and below 19 years old, and there were no differences between females and males (Prabowo et al., 2020). As a binomial factor can determine the indication of adult age (e.g., above or below a certain age), an application of a classification model, such as SVM, can be applied.

5. CONCLUSION

In conclusion, the accuracy of the polynomial kernel SVR outperforms the linear kernel using I$_{3M}$ information with degree = 3, c = 0.25, resulting in an R^2 value of 0.64, *RMSE* of 1.588 and MAE of 1.25 years. The addition of a sex predictor in the model reduces the accuracy of the polynomial kernel. The choice of kernel parameters for SVR must be set independently in each population, measurement method, and measured tooth as the dentition growth differs between each population. Further research should aim for a more extensive study sample and explores alternative statistical methods in processing dental age data to estimate an individual chronological age, regardless of sex.

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