# Hypertension Status Model with Bayesian Adaptive LASSO Binary Quantile Regression Using Asymmetric Laplace Distribution

Lilis Harianti Hasibuan, Ferra Yanuar, Dodi Devianto, Maiyastri

*Abstract*— **Binary quantile regression is one of the widely applied methods in the last decade due to the attractive features of this method for researchers, as it is not affected by outlier values, meaning it is considered one of the robust methods, and provides more details about the effect of independent variables on dichotomous or binary dependent variables. In this study, a Bayesian method is hybrid binary quantile regression, binary quantile regression LASSO, and binary quantile regression adaptive LASSO for variable selection and estimation. The error follows an Asymetric Laplace distribution. The method will be applied to model the hypertension status data. This study used 635 patients of hypertension obtained from Arasuka Solok Hospital, West Sumatra, Indonesia. This study proved that Bayesian Adaptive LASSO binary quantile regression resulted smallest value of mean square error (MSE) than those produced Bayesian LASSO binary quantile regression and Bayesian binary quantile regression. Model hypertension status in Arosuka Solok Hospital is significantly influenced by weight, age, cholesterol, smoking and blood sugar levels. At quantile 0.05, increase in age for 1 year, the level of hypertension status increases by 2.360 times. If there is an increase in body weight by 1 kg, the hypertension increases by 2.046 times. If there is a 1 mg/dL increase in cholesterol, the hypertension level increases by 1.289 times. If there is a 1mg/dL increase in Triglyceride, the hypertension level increases by 1.150 times. If there is a 1 mg% increase in blood sugar levels, the hypertension level increases by 1.633 times. It is concluded that binary Bayesian adaptive LASSO quantile regression has the best performance than other methods in modeling the hypertension case.**

*Index Terms*—**Hypertension status; binary, Bayesian quantile regression, Adaptive LASSO.**

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## I. Introduction

Hypertension is the leading cause of cardiovascular disease and premature death worldwide, due to the widespread use of antihypertensive drugs, the global average blood pressure (BP) has remained constant or slightly decreased over the past four decades [1]. Hypertension can be defined as persistent blood pressure where the systolic pressure is above 140 mmHg and the diastolic pressure is above 90 mmHg [2]. Hypertension is a non-communicable disease that is an important health problem worldwide due to its high and increasing prevalence and association with cardiovascular disease, stroke, retinopathy, and kidney disease.

Hypertension is a disease that affects almost 25% of adults. The prevalence of hypertension is predicted to increase by 60% by 2025, which is around 1.56 thousand people. Patients and 95% were primary hypertension [3]. Hypertension prevalence data nationally is 34.1%. Hypertension in West Sumatra is 25.1%, for Solok City is 31.6% and is ranked 3rd out of 19 districts and cities in West Sumatra [4]. Minangkabau ethnicity has distinctiveness in its traditions and culture. Traditional food Minangkabau traditional foods such as rendang are claimed to be high in saturated fat. The coconut oil and coconut milk used as the main ingredients to make rendang are the main source of rich in saturated fatty acid [5]. this reason, it is necessary to identify the factors that affect hypertension status to provide additional information to the community to avoid factors that cause hypertension so that hypertension cases decrease. Solok City has the highest number of hypertension cases in West Sumatra [6]. The method used to see the mathematical relationship between the independent variable and the dependent variable is regression analysis [7][8].

Classical regression analysis can model data if the classical assumption of normality is met. In fact, in the field, there are many data that violate the assumption of normality. In modeling hypertension status (yes or no) which is binary, it cannot be modeled with ordinary regression methods or least squares methods because it clearly violates the assumption of normality. Modeling data that violates these classical assumptions can be overcome by quantile regression [9][10][11][12]. In quantile analysis, the estimated regression model can be explained by the relationship between the independent variable and the dependent variable at various quantiles [13]. However, quantile regression requires a large

sample size. This limitation of the quantile method is overcome by hybridizing it with the Bayesian method. The Bayesian method is able to estimate model parameters from small data because there is a prior distribution in the estimation process [14]. The hybridization of quantile regression and Bayes method is known as Bayesian quantile regression [15][16][17]. Research using the Bayesian quantile regression method has been done by many previous researchers including [18][19][20][12][21] which discusses variable selection in a binary context sensitive to outliers, heterogeneous values and other anomalies.

Quantile regression has also been applied to censored data to construct the height gain of stunted infants [22][23]. Quantile regression models have also been applied to high-dimensional data with dichotomous response data using normal prior gamma [24]. Quantile regression is a method that handles covariate effects and handles the overfitting problem well [25]. Bayesian quantile regression applied to binary dependent variables is called Binary Bayesian quantile regression. The binary quantile regression method does not require error assumptions in modeling and the estimator is robust to outliers.

Binary quantile regression was introduced by research [26][27]. Binary quantile regression is used also in simple two-step estimation with misinformation of endogenous variables [28]. Bayesian quantile regression with binary scaled response variables still lacks precision, so binary Bayesian quantile regression with regulation parameters or penalty functions using LASSO was developed [29][30]. In this study, a binary Bayesian quantile regression method with adaptive LASSO penalty was applied to model hypertension status of patients from Arosuka Solok Hospital.

## II. Materials and Methods

### A. Data Set

The data used in this study are related to hypertension status obtained from Arosuka Solok Hospital, West Sumatra. The data used is observed directly from the polyclinics of internal medicine and cardiology in 2024. The data used was 635 patients. This secondary data consisted of seven independent variables and one binary dependent variable, namely hypertension status with categories (1 = Hypertension and 0 = Not hypertension). Hypertension status (Y) as a binary dependent variable is based on systolic blood pressure (SBP) and diastolic blood pressure (DBP). It is said to be hypertension if SBP ≥ 140 mmHg and DBP ≥ 90 mmHg.

Hypertension status is assumed to be influenced by gender [31],[32]. Elderly patients with hypertension are predominantly female compared to males [33]. Patients with severe hypertension were also 100% female [34]. Hypertension status is also influenced by age. 15-65 years old are prone to hypertension [35]. Menopausal women have an increase in degenerative diseases, one of which is hypertension [36],[32]. Smoking can cause hypertension due to chemicals contained in tobacco, especially nicotine [37],[38],[39],[40]. Body weight is another factor that is assumed to influence hypertension [41],[42]. Hypertension is also influenced by factors originating from within the human body are cholesterol [43],[44],[45], triglycerides [46],[47],[48], and blood sugar levels [49],[50],[51]. Table 1 below presents a description of the categorical data used in this study as independent variables. Table 1 informs that 43% were male and 36% were smoking.

TABLE 1.
STATISTICS DESCRIPTIVE OF CATEGORICAL VARIABLES

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 281 | 43% |
| | Female | 372 | 57% |
| Smoking | Yes | 235 | 36% |
| | No | 318 | 64% |

### B. Quantile Regression Method

If a vector $\boldsymbol{y} = (y_1, y_2, \dots, y_n)'$ is declared as the dependent variable and $\boldsymbol{x} = (x_1, x_2, \dots, x_k)'$ is defined as the independent variable, then the hypothesis model for the $\tau^{th}$ quantile, where $0 < \tau < 1$ with $n$ samples and $k$ predictors for $i = 1,2, \dots, n$ is written as:

$$y_i = \beta_{0\tau} + \beta_{1\tau}x_{i1} + \beta_{2\tau}x_{i2} + \cdots + \beta_{k\tau}x_{ik} + \varepsilon_i. \quad (1)$$

with $\boldsymbol{\beta}(\tau)$ as the parameter vector and $\boldsymbol{\varepsilon}$ as the residual vector. The conditional quantile function $\tau^{th}$ in the quantile regression method is defined as $Q_\tau(\boldsymbol{y}|\boldsymbol{x_i}) = \boldsymbol{x_i'\beta_\tau}$ , the estimated value of the parameters in the quantile regression equation $\widehat{\boldsymbol{\beta}_\tau}$ is obtained by minimizing the following equation [52]:

$$\sum_{i=1}^{n} \rho_\tau(y_i - \boldsymbol{x_i'\beta_\tau}). \quad (2)$$

with $\rho_\tau(u) = u(\tau - I(u < 0))$is the *loss function* with the equation [10]:

$$\rho_\tau(\epsilon) = \varepsilon\big(\tau I(\varepsilon \geq 0) - (1-\tau)I(\varepsilon < 0)\big). \quad (3)$$

$I(.)$ is an indicator function, which has a value of 1 when $I(.)$ is true dan 0 otherwise.

### C. Bayesian Binary Quantile Regression Method

Binary quantile regression was introduced by Benoit et al. [26], which is an extension of quantile regression where the dependent variable is dichotomous or binary and consists of two categories. One of standard notations for Binary quantile regression model for $\tau^{th}$ quantile and $n$ samples and $k$ predictors for $i = 1,2, \dots, n$ is written as:

$$y_i^* = \beta_{0\tau} + \beta_{1\tau}x_{i1} + \beta_{2\tau}x_{i2} + \cdots + \beta_{k\tau}x_{ik} + \varepsilon_i. \quad (6)$$

$$y_i^* = \boldsymbol{x_i'\beta_\tau} + \varepsilon_i. \quad (7)$$

where $\boldsymbol{x} = (x_{i1}, x_{i2}, \dots, x_{ik})'$ is independent variable for sample for $i = 1,2, \dots, n$, and $\boldsymbol{\beta}(\tau)$ the parameter vector and $\boldsymbol{\varepsilon}$ as the residual vector and$y_i$ is the observed response of $i^{th}$ subject determined by the latent unobserved response $y_i^*$,

$$y_i = \begin{cases} 1, \text{if } y_i^* \geq 0 \\ 0, \text{otherwise.} \end{cases} \quad (8)$$

combining the quantile regression technique with the binary selection regression model, the following binary quantile regression models can be obtained:

$$Q_\tau(y_i^*|x_i) = \boldsymbol{x_i'\beta_\tau} + \varepsilon_i, \quad (9)$$

where, $Q_\tau(y_i^*|x_i) = \inf\{(y_i|F(y_i|x_i) \geq \tau)\}$ is conditional quantile, $\beta_\tau$ is parameter at the $\tau^{th}$ quantile. Because the latent variable $y_i^*$is not observable, it is not possible to use formula (9) to estimate the parameters directly. Based on the

invariance of quantile, the following transformations can be performed:

$$Q_\tau(y_i|x_i) = Q_\tau(h(y_i^*|x_i) = h(Q_\tau(y_i^*|x_i) = h(x_i'\beta_\tau). \quad (10)$$

where $h(x_i'\beta_\tau) = I(x_i'\beta_\tau > 0)$. Let $\rho_\tau(u) = \frac{|u|-(2p-1)u}{2}$ is a test function. The parameter $\beta_\tau$ is determined by the following formula [53]:

$$\sum_{i=1}^{n} \rho_\tau(y_i - h(\boldsymbol{x_i'\beta_\tau})). \quad (11)$$

where $h(\boldsymbol{x_i'\beta_\tau}) = I(\boldsymbol{x_i'\beta_\tau}>0)$ is indicator variable equal 1 if $I(\boldsymbol{x_i'\beta_\tau})$ is true and 0 for otherwise.

Yu and Moyeed [15] suggested that the process of minimizing the loss function of quantile regression is equivalent to maximizing the likelihood function of the Asymmetric Laplace Distribution (ALD) because the loss function in quantile regression is identical to the ALD likelihood function. ALD is used in the process of forming a random variable $\varepsilon$ is ALD distributed with a likelihood density function $f(\varepsilon)$ is:

$$f_\tau(\varepsilon) = \tau(1-\tau)\exp(-\rho_\tau(\varepsilon)). \quad (12)$$

with $0 < \tau < 1$ and $\rho_\tau(\varepsilon)$ being the loss function with $\varepsilon$ being the error of the estimation and $I(\varepsilon)$ being the indicator function. ALD has a combined representation of several distributions, namely based on the exponential and normal distributions used in forming the likelihood function.
The likelihood function so that the estimator becomes more effective and natural or close to the true value so that the correct estimation process can be produce. The ALD distribution is one of the continuous probability distributions. Suppose Z is a random variable with exponential distribution ($Z\sim exp\,(1)$) and U is a random variable with standard normal distribution $U\sim N\,(0,1)$. If $\varepsilon$ is an ALD distributed random variable then $\varepsilon$ can be expressed in the following equation:

$$\varepsilon = \theta z + pu\sqrt{z}. \quad (13)$$

where $\theta = \frac{1-2\tau}{(1-\tau)\tau}$ and $p^2 = \frac{2}{(1-\tau)\tau}$ [15]. Based on equation (14) , the likelihood function used in parameter $\boldsymbol{\beta}$ estimation for the $\tau^{th}$ quantile in the Bayesian quantile regression analysis is formulated in equation (9) as follows [30]:

$$L(\boldsymbol{y_i^*|\beta,\sigma,v}) = \left(\prod_{i=1}^{n}(\sigma v_i)^{-\frac{1}{2}}\right)\left(\exp\left(-\frac{(y_i^* - (\boldsymbol{x_i'\beta_\tau} + \theta v_i))^2}{2p^2\sigma v_i}\right)\right). \quad (14)$$

with $\sigma > 0$ as the scale parameter and dan $v_i = \sigma z_i$ spreading exp *(σ)* distribution. Based on equation (14) the full conditional distribution of $y_i^*$is truncated normal distribution:

$$\boldsymbol{y_i^*|\beta,\sigma,v} = \begin{cases} N(\boldsymbol{x_i'\beta_\tau} + \theta v_i, p^2\sigma v_i)I(y_i^* > 0), \text{if } \boldsymbol{y_i} = 1 \\ N(\boldsymbol{x_i'\beta_\tau} + \theta v_i, p^2\sigma v_i)I(y_i^* > 0), \text{if } \boldsymbol{y_i} = 0 \end{cases}. \quad (15)$$

The prior distribution used in this study are $\boldsymbol{\beta}_\tau\sim N(b_0, B_0)$, $v_i\sim\exp(\sigma)$ and $\sigma\sim IG(a,b)$. While, posterior distribution for each prior are as follows:

$$\begin{aligned}
&(\boldsymbol{\beta}|,\sigma,v,\boldsymbol{y_i^*})\sim N[(\boldsymbol{B_0^{-1}} + \boldsymbol{x_i}(p^2\sigma v)^{-1}\boldsymbol{x_i'})^{-1}\left(\boldsymbol{B_0^{-1}b_0} + \boldsymbol{x_i}(p^2\sigma v)^{-1}x_i')^{-1}y_i^* - x_i(p^2\sigma v)^{-1}\theta v_i\right), (\boldsymbol{B_0^{-1}} + \boldsymbol{x_i}(p^2\sigma v)^{-1}\boldsymbol{x_i'})^{-1}],\\
&(v_i|\boldsymbol{\beta},\sigma,\boldsymbol{y_i^*})\sim GIG(\tfrac{1}{2}, \left(\frac{(y_i^*-x_i'\beta_\tau)^2}{p^2\sigma}\right), (\tfrac{2}{\sigma} + \frac{\theta^2}{p^2\sigma})),\\
&(\sigma|\boldsymbol{\beta},\boldsymbol{v},\boldsymbol{y_i^*})\sim IG(a + \tfrac{3n}{2}, (b + \textstyle\sum_{i=1}^{n} v_i + \sum_{i=1}^{n} + \left(\frac{(y_i^*-(x_i'\beta_\tau+\theta v_i))^2}{2p^2\sigma}\right)).
\end{aligned} \quad (16)$$

*D. Bayesian LASSO Binary Quantile Regression Method*

Mathematically, estimates of Bayesian LASSO binary quantile regression parameter can be calculated by [30],[26]:

$$\beta_{LASSO} = \min_{\beta\epsilon\mathbb{R}} \textstyle\sum_{i=1}^{n}\rho_\tau(\boldsymbol{y_i^*} - \boldsymbol{x_i'\beta}) + \lambda\sum_{j=1}^{k}|\beta_j|. \quad (17)$$

where $\lambda$ is a non-negative variable penalty coefficient. Prior distribution $\boldsymbol{\beta}_\tau, \eta^2, \zeta, \sigma, \boldsymbol{s}, \boldsymbol{v}, \delta$ used for *n*-th sample with *k* predictor according to for used in Bayesian LASSO binary quantile regression is:

$$\begin{aligned}
&f(\beta|\eta^2, s_j) = \prod_{j=1}^{k}\int_0^\infty \frac{1}{\sqrt{2\pi s_j}} exp\,(-\frac{{\beta_j}^2}{2s_j})\frac{\eta^2}{2} exp\,(\frac{-\eta^2}{2}s_j)ds_j \quad ,\\
&f(\eta^2|\delta,\zeta) = \frac{\zeta^\delta}{\Gamma(\delta)}\eta^{2(\delta-1)}\exp(-\zeta\eta^2),\\
&f(\zeta|\delta) = 1,\\
&f(\sigma) = \sigma^{a_1^{-1}}\exp(-a_2\sigma),\\
&f(s_j|\eta^2) = \frac{\eta^2}{2}\exp\left(-\frac{\eta^2}{2}s_j\right),\\
&f(v_i|\sigma) = \sigma\exp(-v_i\sigma),\\
&f(\delta|\zeta,\eta^2) = \frac{(\zeta\eta^2)^\delta}{\Gamma(\delta)}.
\end{aligned} \quad (18)$$

with $\eta = \sigma\lambda$, $\eta^2\sim Gamma(\eta^2, \zeta^{-1})$, $\boldsymbol{s} = (s_1, \dots, s_k), i = 1,2 \dots k$, $\boldsymbol{v} = (v_1, \dots, v_n), \sigma > 0, a_1 > 0, a_2 > 0, \eta^2 > 0, \zeta > 0, \delta > 0$. Based on equation (18), the joint posterior distribution Bayesian LASSO binary quantile regression is obtained as follows:

$$\begin{aligned}
&f(\boldsymbol{\beta_\tau}|\eta^2,\zeta,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim N(\frac{\sigma\sum_{i=1}^{n}\hat{y}_{ij}x_{ij}}{2v_i}, \frac{1}{\frac{1}{s_j}+\sigma\sum_{i=1}^{n}\frac{x_{ij}{}^2}{2v_i}}),\\
&f(\eta^2|\boldsymbol{\beta_\tau},\zeta,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim Gamma\left(\zeta + k, v + \textstyle\sum_{j=0}^{k}\frac{s_j}{2}\right),\\
&f(v|\boldsymbol{\beta_\tau},\eta^2,\zeta,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim Gamma(\zeta,\eta^2),\\
&f(\zeta|\boldsymbol{\beta_\tau},\eta^2,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim Gamma(\zeta,\eta^2),\\
&f(v_i|\boldsymbol{\beta_\tau},\eta^2,v,\zeta,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim GIG\left(\frac{1}{2}, \left(\frac{(y_i^*-x_i'\beta_\tau)^2}{p^2\sigma}\right), \left(\frac{2}{\sigma} + \frac{\theta^2}{p^2\sigma}\right)\right),\\
&f(s_i|\boldsymbol{\beta_\tau},\eta^2,v,\zeta,\sigma,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim GIG\left(\frac{1}{2},\beta_j^2,\eta^2\right),\\
&f(\sigma|\boldsymbol{\beta_\tau},\eta^2,v,\zeta,\boldsymbol{s},\boldsymbol{v},\delta,\boldsymbol{y^*})\sim GIG\left(a + \frac{3n}{2}, (b + \sum_{i=1}^{n}\left(\frac{(y_i^*-(x_i'\beta_\tau+\sigma v_i)}{2p^2v_i}\right)^2 + v_i\right).
\end{aligned} \quad (19)$$

*E. Bayesian Adaptive LASSO Binary Quantile Regression Method*

To estimates of Bayesian Adaptive LASSO binary quantile regression parameters can be calculated by study [30]:

$$\beta_{ALASSO}=\min_{\beta\epsilon\mathbb{R}} \sum_{i=1}^{n} \rho_\tau(\boldsymbol{y_i^*} - \boldsymbol{x_i'\beta}) + \sum_{j=1}^{k} \lambda_i|\beta_j|. \quad (20)$$

where $\lambda_i$ is a non-negative variable penalty coefficient, $i = 1,2,..,k$. Prior distribution for $\boldsymbol{\beta}_\tau, {\lambda_j}^2, \zeta, \sigma, \boldsymbol{s}, \boldsymbol{v}, \delta$ used in Bayesian Adaptive LASSO binary quantile regression is as follows [54]:

$$\begin{aligned}
&f(\boldsymbol{\beta}|{\lambda_j}^2, s_j)\\
&= \prod_{j=1}^{k} \int_0^\infty \frac{1}{\sqrt{2\pi s_j}} exp\,(-\frac{{\beta_j}^2}{2s_j}) \frac{{\lambda_j}^2}{2} exp\,(\frac{-{\lambda_j}^2}{2} s_j) ds_j,\\
&f(\zeta|\delta) = 1,\\
&f(\sigma) = \sigma^{a_1^{-1}} \exp(-a_2\sigma),\\
&f(s_j|{\lambda_j}^2) = \frac{{\lambda_j}^2}{2} \exp\left(-\frac{{\lambda_j}^2}{2} s_j\right),\\
&f(v_i|\sigma) = \sigma \exp(-v_i\sigma),\\
&f(\delta|\zeta, {\lambda_j}^2) = \frac{(\zeta{\lambda_j}^2)^\delta}{\Gamma(\delta)}
\end{aligned} \quad (21)$$

with $\boldsymbol{s} = (s_1, \dots, s_k), i = 1,2, \dots, k$, $\boldsymbol{v} = (v_1, \dots, v_n)$, $\sigma > 0$, $a_1 > 0, a_2 > 0, {\lambda_j}^2 \geq 0, \zeta > 0, \delta > 0$

Based on equation (21), the joint posterior distribution Bayesian Adaptive LASSO binary quantile regression is obtained as follows:

$$\begin{aligned}
&f((\beta|\boldsymbol{y_i^*}, s_{j,} v_i, \sigma) \sim N(\bar{\beta}_j, \bar{\sigma}_j),\\
&\text{with, } \bar{\sigma}_j{}^2 = \left(\sigma \sum_1^n \frac{x_{ij}{}^2}{2v_i} + \frac{1}{s_j}\right)^{-1},\\
&\bar{\beta}_j = \\
&\bar{\sigma}_j{}^2 \sigma \sum_{i=1}^n \frac{(y_i^* - \sum_{i\neq j} x_{iI}\beta_I - \zeta v_i)}{2v_i},\\
&f((\sigma|\boldsymbol{y_i^*}, s_{j,} v_i, \sigma) \sim Gamma\left(\frac{3}{2}n + a_1,\ \sum_{i=1}^n \left(\frac{(y_i^* - \zeta v_i)^2}{4v_i} + p(1-p)v_i + b_1\right)\right),\\
&f({\lambda_j}^2|s_{j,}\ \sigma) \sim Gamma(1 + a_0, \frac{s_{j,}\sigma}{2} + b_0),\\
&f((s_{j,}|{\lambda_j}^2, \beta, \sigma,) \sim GIG\left(\frac{1}{2} + \beta_j^2, \sigma{\lambda_j}^2\right),\\
&f((v^{-1}|\boldsymbol{y_i^*}, \beta, \sigma,) \sim GIG\left(\frac{1}{2}, \frac{\sigma}{2}, \frac{\sigma(y_i^* - x_i'\beta)^2}{2}\right),\\
&f((s_{j,}|\boldsymbol{y_i^*}, \beta, \sigma,) \sim GIG\left(\frac{1}{2}, \frac{\sigma}{2}, \frac{\sigma(y_i^* - \boldsymbol{x_i'\beta})^2}{2}\right),
\end{aligned} \quad (22)$$

The multiple roots algorithm proposed by Yun [55] will be used to sample from it, and the constraint condition $\|\beta\|_1$ will be imposed value. The steps are follows: set initial value $\boldsymbol{\beta}, v, \sigma, {\lambda_j}^2 (j = 1,2, \dots, k)$ ; from the $f((\boldsymbol{y_i^*}|y, \boldsymbol{\beta}, v_i, \sigma,)$ generate $\boldsymbol{y_i^*}, i = 1,2, \dots, n$ ; from $f(v^{-1}|\boldsymbol{y_i^*}, \boldsymbol{\beta}, \sigma,)$ generate $v^{-1}, i = 1,2, \dots, n$; from $f((\sigma|\boldsymbol{y_i^*}, s_{j,} v_i, \sigma)$generate $\sigma$; from $f((\boldsymbol{\beta_j}|\boldsymbol{y_i^*}, s_{j,} v_i, \sigma)$ generate $\beta_j$; and the constraint condition $\beta = 1, j = 1,2, \dots, k$; from $f((s_{j,}|{\lambda_j}^2, \boldsymbol{\beta}, \sigma)$ generate $s_{j,}, j = 1,2, \dots, k$ ; from $f({\lambda_j}^2|s_{j,}\ \sigma)$ generate ${\lambda_j}^2, j = 1,2, \dots, k$ ; return the second to seventh step.

## III. Result and Discussion

In this section, we apply the proposed Bayesian approach for Bayesian binary quantile regression (BBQR), Bayesian LASSO binary quantile regression (BBLQR) and Bayesian Adaptive LASSO binary quantile regression (BBALQR) for find the model hypertension status. The parameters estimation process was carried out by determining mean and variance of each parameter formulated in the posterior distribution. Table 2 present the parameters estimation results, with confidence interval width of 95% for quantiles 0.05; 0.25; 0.55; 0.75; 0.95.

Based Table 2, the BBQR, BBLQR and BBALQR methods obtained the variable gender ($X_{1D1}$) statistically not significant in influencing hypertension status in all quantiles, namely quantiles 0.05; 0.25; 0.55; 0.75; and 0.95. BBQR method variable age ($X_2$) statistically significant in quantiles 0.25; 0.55; 0.75. BBLQR method variable age ($X_2$)statistically not significant in influencing hypertension status in all quantiles and BBALQR method resulted that variable age ($X_2$) statistically significant in influencing hypertension status in all selected quantile. BBQR, BBLQR and BBALQR methods variable smoking ($X_{3D1}$) not statistically significant in all quantile.

The BBQR the variable body weight ($X_4$) statistically not significant in influencing hypertension status in all quantiles, namely quantiles 0.05; 0.25;0.75, BBLQR methods obtained the variable body weight ($X_4$) statistically not significant in influencing hypertension status in all quantiles and BBALQR method obtained variable body weight ($X_4$) is statistically significant in influencing hypertension status in all quantiles. The BBQR the variable cholesterol ($X_5$) statistically not significant in influencing hypertension status in all quantiles, namely 0.05; 0.25;0.75. BBLQR methods obtained the variable cholesterol ($X_5$) statistically not significant in influencing hypertension status in all quantiles and while BBALQR method obtained variable cholesterol ($X_5$) is statistically not significant in influencing hypertension status only in 0.05 and 0.95 quantile.

The BBQR, BBLQR obtained variable triglyceride ($X_6$) statistically not significant in influencing hypertension status in all quantiles, namely quantiles 0.05; 0.25; 0.55; 0.75; and 0.95 and BBALQR method obtained variable triglyceride ($X_6$) is statistically significant in affecting hypertension status in quantiles 0.55;0.75 and 0.95. The BBQR, BBLQR obtained variable blood sugar levels ($X_7$) statistically not significant in influencing hypertension status in all quantiles, namely quantiles 0.05; 0.25; 0.55; 0.75; and 0.95, BBALQR method variable blood sugar levels ($X_7$) is statistically significant in affecting hypertension status in all quantile. Table present the results of the 95% confidence interval width estimates generated from this method. Next, the comparison of error values from the application of three methods is presented in Table 3 below.

TABEL 2.
THE PARAMETERS ESTIMATED AND WIDTH OF 95% CONFIDENCE INTERVAL USING BBQR, BBLQR, and BBALQR

| Independent Variables | BBQR | | BBLQR | | BBALQR | |
|---|---|---|---|---|---|---|
| | **Estimated Mean $(\widehat{\boldsymbol{\beta}})$** | Width 95% CI | **Estimated Mean $(\widehat{\boldsymbol{\beta}})$** | Width 95% CI | **Estimated Mean $(\widehat{\boldsymbol{\beta}})$** | Width 95% CI |
| | | | **$\tau = 0.05$** | | | |
| Intercept | **-5.613*** | 4.210 | -0.004 | 0.012 | **-299.877*** | 483.066 |
| Gender$(X_{1D1})$ | 0.081 | 0.135 | -0.0002 | 0.001 | 0.369 | 8.163 |
| Age $(X_2)$ | 0.014 | 0.029 | 0.00001 | -3.42e-05 | **0.859*** | 0.986 |
| Smoking $(X_{3D1})$ | 0.169 | 0.379 | -0.00009 | 0.001 | 8.610 | 3.015 |
| Body weight $(X_4)$ | 0.007 | 0.013 | -0.000001 | 1.744e-05 | **0.716*** | 0.769 |
| Cholesterol $(X_5)$ | 0.002 | 0.004 | 0.000004 | -8.133e-06 | **0.254*** | 0.907 |
| Triglyceride $(X_6)$ | -0.001 | 0.002 | -0.000005 | 2.436e-05 | 0.140 | 0.78 |
| Blood sugar levels $(X_7)$ | 0.002 | 0.007 | -0.000009 | 3.301e-05 | **0.491*** | 1.019 |
| | | | **$\tau = 0.25$** | | | |
| Intercept | **-271.685*** | 2.008 | -0.0121 | 0.033 | **-303.529*** | 409.461 |
| Gender$(X_{1D1})$ | 0.046 | 0.082 | 0.0005 | 0.0008 | -2.441 | 16.92 |
| Age $(X_2)$ | **0.014*** | 0.016 | 0.0001 | 0.0002 | **0.864*** | 0.991 |
| Smoking $(X_{3D1})$ | 0.205 | 0.426 | 0.0015 | 0.003 | 1.124 | 8.817 |
| Body weight $(X_4)$ | 0.009 | 0.018 | 0.00004 | 0.0001 | **0.847*** | 0.927 |
| Cholesterol $(X_5)$ | 0.002 | 0.004 | 0.00001 | 4.130e-05 | 0.319 | 0.93 |
| Triglyceride $(X_6)$ | -0.00001 | 0.002 | -0.000002 | 7.677e-06 | 0.403 | 0.941 |
| Blood sugar levels $(X_7)$ | 0.0001 | 0.001 | 0.00001 | 3.802e-05 | **0.755*** | 0.944 |
| | | | **$\tau = 0.55$** | | | |
| Intercept | **-155.370*** | 1.447 | **0.808*** | 0.459 | **-307.137*** | 391.607 |
| Gender$(X_{1D1})$ | 0.015 | 0.035 | -0.002 | 0.008 | -1.378 | 6.795 |
| Age $(X_2)$ | **0.013*** | 0.013 | 0.001 | 0.003 | **1.088*** | 0.611 |
| Smoking $(X_{3D1})$ | 0.210 | 0.435 | 0.019 | 0.052 | 0.711 | 6.781 |
| Body weight $(X_4)$ | **0.009*** | 0.018 | 0.0009 | 0.002 | **0.575*** | 0.638 |
| Cholesterol $(X_5)$ | **0.002*** | 0.004 | 0.0001 | 0.0004 | 0.468 | 0.825 |
| Triglyceride $(X_6)$ | 0.0002 | 0.0002 | -0.00002 | 0.0001 | **0.699*** | 0.748 |
| Blood sugar levels $(X_7)$ | 0.0003 | 0.0006 | -0.00003 | 0.0001 | **0.989*** | 0.206 |
| | | | **$\tau = 0.75$** | | | |
| Intercept | **-109.947*** | 2.147 | **0.987*** | 0.075 | **-291.114*** | 368.275 |
| Gender$(X_{1D1})$ | 0.002 | 0.039 | -0.0002 | 0.001 | 2.516 | 7.036 |
| Age $(X_2)$ | **0.016*** | 0.019 | 0.00008 | 0.0002 | **0.951*** | 0.621 |
| Smoking $(X_{3D1})$ | 0.267 | 0.557 | 0.001 | 0.0027 | 13.118 | 21.223 |
| Body weight $(X_4)$ | 0.012 | 0.023 | 0.00007 | 0.0002 | **0.716*** | 0.547 |
| Cholesterol $(X_5)$ | 0.003 | 0.005 | 0.00001 | 4.123e-05 | 0.567 | 0.967 |
| Triglyceride $(X_6)$ | -0.00002 | 0.0001 | 0.0000004 | 7.345e-06 | **0.721*** | 0.753 |
| Blood sugar levels $(X_7)$ | 0.00009 | 0.0001 | 0.000002 | 4.7495e-06 | **1.073*** | 0.159 |
| | | | **$\tau = 0.95$** | | | |
| Intercept | 196.37 | 3.990 | **0.989*** | 0.035 | **-236.146*** | 324.122 |
| Gender$(X_{1D1})$ | -0.0017 | 0.029 | 0.0003 | 0.0001 | 2.637 | 6.042 |
| Age $(X_2)$ | 0.0016 | 0.032 | 0.0002 | 0.0006 | **0.608*** | 0.984 |
| Smoking $(X_{3D1})$ | 0.2625 | 0.545 | 0.0003 | 0.0015 | 1.379 | 3.266 |
| Body weight $(X_4)$ | 0.0184 | 0.021 | 0.00001 | 5.5496e-05 | **0.804*** | 0.354 |
| Cholesterol $(X_5)$ | 0.0026 | 0.005 | 0.000004 | 1.7429e-05 | **0.616*** | 0.915 |
| Triglyceride $(X_6)$ | -0.00001 | 0.0006 | 0.000005 | 2.4975e-05 | **0.709*** | 0.758 |
| Blood sugar levels $(X_7)$ | -0.0001 | 0.0002 | 0.000008 | 3.3103e-05 | **1.094*** | 0.236 |

*Significant at $\alpha = 0.05$.

TABEL 3.
MSE FOR EACH SELECTED QUANTILE MODEL

| Quantile | Methods | MSE |
|---|---|---|
| $\tau = 0.05$ | BBQR | 18.963 |
| | BBLQR | 0.562 |
| | BBALQR | **0.282** |
| $\tau = 0.25$ | BBQR | 2.153 |
| | BBLQR | 0.553 |
| | BBALQR | **0.530** |
| $\tau = 0.55$ | BBQR | 0.435 |
| | BBLQR | 0.409 |
| | BBALQR | **0.402** |
| $\tau = 0.75$ | BBQR | 0.695 |
| | BBLQR | 0.442 |
| | BBALQR | **0.430** |
| $\tau = 0.95$ | BBQR | 6.264 |
| | BBLQR | 0.446 |
| | BBALQR | **0.435** |

TABLE 4.
ODD RATIO IN QUANTILE $\tau = 0.05$

| Independent Variables | Mean $(\widehat{\beta})$ | Odd Ratio |
|---|---|---|
| Gender$(X_{1D1})$ | 0.369 | 1.446 |
| Age $(X_2)$ | 0.859 | 2.360 |
| Smoking $(X_{3D1})$ | 8.610 | 5.486 |
| Body weight $(X_4)$ | 0.716 | 2.046 |
| Cholesterol $(X_5)$ | 0.254 | 1.289 |
| Triglyceride $(X_6)$ | 0.140 | 1.150 |
| Blood sugar levels $(X_7)$ | 0.491 | 1.633 |

Based on the results presented in Table 3, we see that BBALQR produce the smallest MSE than BBQR and BBLQR. Based Table 2 and 3 the best model obtained for hypertension status in Arosuka Hospital is a model using the Binary Bayesian Adaptive LASSO quantile regression at quantile 0.05 which is formulated:

$$Logit(p_i) = -299.877 + 0.369X_{1D1} + 0.859X_2 + 8.610X_{3D1} + 0.716X_4 + 0.254X_5 + 0.140X_6 + 0.491X_7. \quad (23)$$

Based equation (23) can be interpreted by looking at odds ratio values in Table 4. Based on the Table 4 we can inform that if there is an increase in age $X_2$ for 1 year, the level of hypertension status increases by 2.360 times. If there is an increase in body weight $X_4$ by 1 kg, the hypertension increases by 2.046 times. If there is a 1 mg/dL increase in cholesterol $X_5$, the hypertension level increases by 1.289 times. If there is a 1mg/dL increase in triglyceride $X_6$, the hypertension level increases by 1.150 times. If there is a 1mg% increase in blood sugar levels $X_7$, the hypertension level increases by 1.633 times. From the BBALQR model obtained in accordance with the model above, it is obtained that the status of hypertension in Arosuka Solok hospital, we can control the significant independent variables to reduce the risk of developing hypertension.

The Bayesian Adaptive LASSO binary quantile regression method (BBALQR) using MCMC Gibbs Sampling algorithm is proven to be easier and more practical to apply and produces better estimators than estimators produced by ordinary quantile regression. From the case study described above, the best model is obtained at quantile 0.05, because it has small MSE. Variables that significantly affect hypertension status in Arosuka Solok Hospital are weight, age, cholesterol, smoking and blood sugar levels based on simulations conducted with this method. However, we are convinced that also in many other fields researchers could benefit from attractive properties of the Bayesian Adaptive LASSO combined with binary quantile regression.

## IV. Conclusions

This study aims to model hypertension status as a binary response variable with a Binary Bayesian Quantile Regression approach combined with the Adaptive Lasso technique. The results show that this approach is able to effectively handle data with non-normal distribution, heteroscedasticity, as well as provide flexibility in evaluating the effect of predictor variables on various quantiles of the conditional distribution.

The Bayesian Binary Quantile Regression with Adaptive Lasso method also proved to be able to perform variable selection automatically and efficiently, resulting in a parsimonious yet accurate model. Several significant predictor variables for hypertension status were identified at certain quantiles, indicating that the effect of predictor variables on hypertension is not homogeneous across the distribution of patient conditions.

In this paper, we have presented a Bayesian approach for binary quantile regression, binary quantile regression LASSO, and binary quantile regression Adaptive LASSO. The advantages of this approach are first, compare three methods the estimation and variable selection procedure is insensitive with regard to outliers, heteroskedasticity, or other anomalies that can break existing methods down. And second, the selection of predictive variables affecting the dependent variable without sensitivity to abnormal values, unlike other methods such as the method of ordinary least square.

A Bayesian approach to this problem is to put Laplace prior distribution on the regression parameters. The best model is obtained at quantile 0.05, because it has small MSE. The smallest MSE value is 0.282. While the factors that significantly affect hypertension status are age $X_2$, body weight $X_4$, cholesterol $X_5$, triglyceride $X_6$, and blood sugar levels $X_7$.

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