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SINGLE-STACKED SUPPORT VECTOR REGRESSION-BAYESIAN-BASED MODELS FOR UNEMPLOYMENT TREND ANALYSIS IN MALAYSIA'S YOUTH LABOR MARKET

(*Algoritma Ramalan Berasaskan Bayesian-Regresi Vektor Sokongan Bertindan Tunggal untuk Analisis Rentetan Pengangguran dalam Pasaran Buruh Belia di Malaysia*)

ZUN LIANG CHUAN*, CHIA KUANG LEE, WENDY LING SHINYIE,
NORISZURA ISMAIL & SOO-FEN FAM

ABSTRACT

In response to the evolving dynamics of the labor market shaped by natural disasters such as the Coronavirus Disease 2019 (COVID-19) pandemic, rapid technological progress, and the emergence of the Fourth Industrial Revolution (IR4.0), and given the very limited sample size of the unemployment dataset (less than 30 observations), this article introduces two advanced models that combine Support Vector Regression (SVR) with Bayesian statistical methods, namely the Single-Stacked SVR-Empirical Bayesian Beta-Binomial (SSVREBB) and the Single-Stacked SVR-Hierarchical Bayesian Binomial Proportion (SSVRHBB). These models are designed to handle data-limited environments while maintaining reliable predictive performance. They demonstrate superior flexibility in capturing both linear and nonlinear patterns and provide explicit quantification of prediction uncertainty, outperforming conventional time series, machine learning, and deep learning benchmarks. A VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)-based Taguchi optimisation framework is employed to identify the best-performing model configuration. The empirical analysis utilises annual unemployment data from 1995 to 2020, disaggregated by states, regions, and gender in Malaysia. The results indicate persistently high youth unemployment, particularly among females in Sabah (SBH), mainly due to gaps in education quality and skills mismatches. While the study focuses on the national context, it offers insights for policymakers aiming to reduce gender disparities, enhance female labor force participation, and support equitable employment opportunities in data-limited environments. In alignment with relevant United Nations Sustainable Development Goals (SDGs), specifically SDG1 (No Poverty), SDG4 (Quality Education), SDG5 (Gender Equality), and SDG8 (Decent Work and Economic Growth), this research demonstrates the potential of innovative predictive modelling to inform evidence-based labor market policies.

Keywords: Single-Stacked SVR-Bayesian-based models; prediction uncertainty; labor force market; inclusive growth; policy insights

ABSTRAK

Sebagai tindak balas kepada dinamik pasaran tenaga kerja yang berkembang akibat bencana alam seperti pandemik Penyakit Koronavirus 2019 (COVID-19), kemajuan teknologi yang pesat, dan kemunculan Revolusi Industri Keempat (IR4.0), serta mengambil kira saiz sampel yang sangat terhad bagi set data pengangguran (kurang daripada 30 pemerhatian), makalah ini memperkenalkan dua model canggih yang menggabungkan Regresi Vektor Sokongan (SVR) dengan kaedah statistik Bayesian, iaitu SVR-Bayes Empirik Beta-Binomial Bertindan Tunggal (SSVREBB) dan SVR-Bayes Hierarki Perkadaran Binomial Bertindan Tunggal (SSVRHBB). Model-model ini direka untuk mengendalikan persekitaran dengan data terhad, di samping mengekalkan prestasi ramalan yang boleh dipercayai. Model ini menunjukkan keluwesan yang unggul dalam mengendalikan corak linear dan tak linear, serta menyediakan pengukuran ketidakpastian ramalan secara eksplisit, mengatasi penanda aras siri masa konvensional, pembelajaran mesin, dan pembelajaran mendalam. Rangka kerja pengoptimuman *Taguchi berasaskan VlseKriterijumska Optimizacija I Kompromisno Resenje* (VIKOR) digunakan untuk mengenal pasti konfigurasi model yang terbaik. Analisis empirikal menggunakan data tahunan dari 1995 hingga 2020, dipecahkan mengikut negeri, wilayah dan jantina di Malaysia. Hasil kajian mendedahkan kadar pengangguran belia yang kekal tinggi, terutamanya di kalangan wanita di Sabah (SBH), yang berakar umbi daripada jurang kualiti pendidikan dan ketidakpadanan kemahiran. Walaupun kajian ini memfokuskan kepada konteks nasional, kajian ini menawarkan pandangan penting kepada penggubal dasar di seluruh dunia dalam usaha menangani ketidaksamaan jantina, meningkatkan penyertaan tenaga kerja wanita, dan menyokong peluang pekerjaan yang adil dalam persekitaran dengan data terhad. Selaras dengan Matlamat Pembangunan Mampan Pertubuhan Bangsa-Bangsa Bersatu (SDGs) yang berkait, khususnya SDG1 (Tiada Kemiskinan), SDG4 (Pendidikan Berkualiti), SDG5 (Kesaksamaan Jantina), dan SDG8 (Pekerjaan yang Baik dan Pertumbuhan Ekonomi), kajian ini menekankan potensi kaedah ramalan inovatif untuk menyokong dasar pasaran tenaga kerja berasaskan bukti.

Kata kunci: model-model berasaskan Bayesian-SVR bertindan tunggal, ketidakpastian ramalan, pasaran tenaga kerja belia; pertumbuhan inklusif; implikasi dasa

1. Introduction

The Coronavirus Disease (COVID-19) pandemic has had a devastating global impact, with over 7 million confirmed deaths from December 2019 to August 2025. This crisis destabilised financial systems and hindered sustainable development, impacting nations at all levels. COVID-19 introduced unprecedented uncertainties, disrupting various areas such as career (Berchin & de Andrade Guerra 2020; Shah *et al.* 2020), economic activities (Shah *et al.* 2020), education (Berchin & de Andrade Guerra 2020; Shah *et al.* 2020), food systems (Berchin & de Andrade Guerra 2020), and health-related quality of life (Kang *et al.* 2020). Small and Medium-sized Enterprises (SMEs) were particularly hard hit, while rising poverty levels and social dysfunction further destabilised societies (Banerjee 2020; Berchin & de Andrade Guerra 2020; Keshky *et al.* 2020). Public anxiety and health concerns restricted movements, reducing household income and sharply increasing unemployment, which in turn decreased consumer spending and detrimentally affected household welfare and the national Gross Domestic Product (GDP) (Banerjee 2020; Keshky *et al.* 2020; Shah *et al.* 2020).

In Malaysia, agriculture was the primary contributor to GDP until the 1970s, when the government shifted focus to export-oriented industries. This transition from inward-oriented trade to industrialisation profoundly reshaped the labor market, with the services sector expanding rapidly in the 1980s to become the largest GDP contributor, surpassing construction, manufacturing, and mining. More recently, the labor market has been influenced by two significant forces: the COVID-19 pandemic and automation technologies associated with the Fourth Industrial Revolution (IR4.0). The unemployment rate rose from 3.3% in 2019 to 4.5% in 2020, before slightly declining to 4.3% in 2021 due to movement restrictions (Rahman *et al.* 2020; Lim 2022). Vulnerable groups include individuals with low education, low income, and the very young or elderly (Rahman *et al.* 2020). Concurrently, the pandemic accelerated the adoption of IR4.0 automation technologies, such as cloud computing, robotics, artificial intelligence (AI), Cyber Physical Systems, and 5G-powered Internet of Things (IoT), creating job uncertainty and complicating predictions of future technological developments. These trends align with the Malaysian government's push to digitise business operations, supported by the Malaysia Digital Economy Corporation (MDEC) (Karr *et al.* 2020; Rahman *et al.* 2020; Yeong *et al.* 2022).

However, existing studies (Dumičić *et al.* 2015; Katris 2020; Ng *et al.* 2023; Yamacli & Yamacli 2023) indicate that no single model, whether traditional or AI-based, is universally optimal for forecasting unemployment rates. Their performance depends on factors such as time horizon, data characteristics, and geographical context (Yamacli & Yamacli 2023). In addition, many conventional approaches typically require relatively large datasets, limiting their applicability in Malaysia, where merely 26 annual observations are available. Moreover, prior studies (Katris 2020; Shapi *et al.* 2021; Lee *et al.* 2022) frequently emphasised predictive accuracy without explicitly distinguishing forecasting from its evaluation, leading to ambiguity regarding the reliance on out-of-sample performance as a proxy for forecasting. Such limitations highlight the need for modelling approaches that effectively address both forecasting and its evaluation in small-sample contexts.

To address these challenges, this article proposes an innovative short-run single-stacked AI-Bayesian-based statistical model integrating Support Vector Regression (SVR) with empirical and hierarchical Bayesian-based models, following the Cross Industry Standard Process for Data Mining (CRISP–DM) framework. Specifically, this article introduces two AI-Bayesian-based models: the Single-Stacked SVR-Empirical Bayesian Beta-Binomial (SSVREBB) and the Single-Stacked SVR-Hierarchical Bayesian Binomial Proportion (SSVRHBB). These models are tailored for Malaysia's annual unemployment rate datasets, which align with a Binomial distribution, and address gaps in the literature regarding hierarchical Bayesian applications, particularly for gender disparities, regional, and state-level differences.

Furthermore, this article proposes an innovative evaluation criterion to identify the most effective model. Specifically, model ranking employs the VIseKriterijuska Optimizacija I Komoromisno Resenje-based (VIKOR-based) Taguchi optimisation algorithm, utilising a Signal-to-Noise Ratio (SNR) transformer for Goodness-of-Fit (GoF) statistics, ensuring that smaller values are preferable. This multi-criteria decision-making approach is more robust than relying solely on GoF statistics, which may lead to locally optimal solutions when conflicts arise.

The proposed single-stacked SVR-Bayesian-based models provide a flexible predictive framework for data-limited environments by integrating machine learning with Bayesian inference and explicitly quantifying prediction uncertainty, enabling more reliable unemployment forecasts compared with conventional approaches. The findings provide insights into Malaysia's unemployment dynamics, particularly identifying vulnerable groups such as the female youth labor force. supporting policy interventions aimed at improving education quality and reducing skills mismatches. Furthermore, the study also aligns with international labor market objectives under the United Nations Sustainable Development Goals (SDGs), including SDG1 (No Poverty), SDG4 (Quality Education), SDG5 (Gender Equality), and SDG8 (Decent Work and Economic Growth), and is consistent with Malaysia's development agenda outlined in the 13th Malaysia Plan (13MP), and the MADANI Economy Framework, which aims to increase women's labor market participation to 60%. To pursue these objectives, the remainder of this article is organised as follows: Section 2 presents the related works; Section 3 describes the theoretical background underpinning the proposed models; Section 4 discusses the empirical results; and Section 5 concludes with final remarks and directions for future research.

2. Related Works

Despite significant transformations in the labor market and the adoption of automation technologies, there remains limited literature forecasting the univariate unemployment rate in Malaysia, particularly concerning gender, regions, and states. The models frequently employed in this literature are primarily traditional statistical models, creating a gap for more advanced techniques to better capture the dynamics of Malaysia's labor market, especially in data-limited environments. For instance, Nasir *et al.* (2006) recommended utilising Holt's exponential smoothing model to forecast the national quarterly unemployment rate. Their comparison of Holt's exponential smoothing model with the Naïve and moving average models indicated that Holt's exponential smoothing model was the most effective statistical model. More than a decade later, Nor *et al.* (2018) utilised quarterly and annual time series datasets to investigate the accuracy of the Naïve, simple exponential smoothing, and Holt's exponential smoothing models in forecasting unemployment rates by gender. In contrast, Ramli *et al.* (2018) assessed the effectiveness of Autoregressive Integrated Moving Average (ARIMA) and Holt's exponential smoothing models for forecasting national annual unemployment rates, finding that the ARIMA model outperformed Holt's exponential smoothing model.

Recently, Yi and Khalid (2022) conducted a comparative study of traditional statistical models, including the Naïve, Holt's exponential smoothing, and ARIMA models, focusing on Malaysia's monthly unemployment rate. Their findings indicated that the Naïve model outperformed both Holt's exponential smoothing and ARIMA models in terms of forecasting accuracy. These traditional statistical models have been extensively employed in the international literature (Dumičić *et al.* 2015; Gostkowski & Rokicki 2021; Ng *et al.* 2023; Tengaa *et al.* 2023; Yamacli & Yamacli 2023; Huruta 2024) due to their effectiveness in handling the characteristics of various datasets. However, a principal limitation of models, such as ARIMA and exponential smoothing-based models, is their general requirement for a large sample size of at least 50 observations (Hanke & Wichern 2013), alongside reliance on pre-defined assumptions about the datasets. Furthermore, selecting an appropriate exponential smoothing model heavily depends on the four key time series components: trend, seasonality, cyclic, and irregularities. In contrast, the Naïve model, while computationally simple, does not account for past observations or patterns in the time series, rendering it incapable of capturing these critical components.

AI-based models have emerged as strong alternatives to traditional approaches in forecasting global behaviour (Bontempi *et al.* 2013). However, their application in the context of Malaysia remains limited. Prominent AI-based models include neural networks (Peláez 2006), the hybridisation of Learning Vector Quantisation (LVQ) and Radial Basis Function Neural Network (RBFNN) (Sharma & Singh 2016), and Neural Network Autoregression (NNAR) (Davidescu *et al.* 2021). These AI-based models offer key advantages over traditional statistical models, particularly in forecasting unemployment rates (Katris 2020; Davidescu *et al.* 2021). AI-based models can capture complex nonlinear relationships within datasets, require no assumptions about dataset distribution, and are robust and adaptive, eliminating the need for dataset transformation when assumptions of traditional statistical models are violated. Nevertheless, despite these advantages, there remains limited research exploring the utilisation of AI-based models in Malaysia.

In summary, previous studies (Dumičić *et al.* 2015; Katris 2020; Ng *et al.* 2023; Yamacli & Yamacli 2023) indicate that no single model, whether traditional or AI-based, is universally optimal for forecasting unemployment rates. The performance of these models depends on factors such as the dataset's time horizon, the underlying time series components, and the geographical context (Yamacli & Yamacli 2023). Both traditional statistical and AI-based models generally require relatively large datasets, which may limit their applicability in data-constrained environments such as Malaysia, where merely 26 annual observations are available. Moreover, some studies (Katris 2020) have primarily focused on predictive accuracy without explicitly distinguishing between forecasting and its evaluation. This distinction has also been emphasised in related literature (Shapi *et al.* 2021; Lee *et al.* 2022), where reliance on out-of-sample performance alone can lead to ambiguity. Such limitations underscore the need for modelling approaches capable of explicitly addressing both forecasting and its evaluation, particularly in small-sample contexts.

3. Research Methodology and Theoretical Background

This section provides an overview of the theoretical framework, focusing on the SSVREBB and SSVRHBB models, as well as the methodological architecture grounded in the CRISP-DM framework utilised in this study. Specifically, the general CRISP-DM framework consists of six key phases: business understanding, data understanding, data preparation, modelling, evaluation, and deployment, which are detailed in the subsequent sections. The rationale for favouring this framework over alternatives such as Knowledge Discovery in Databases (KDD) and Sample, Explore, Modify, Model, and Assess (SEMMA) lies in its iterative flexibility across phases and its comprehensive approach. Furthermore, the CRISP-DM framework has been widely applied across diverse research domains, such as computer science, education economics, finance research, and healthcare (Cheng 2023; Lohaj *et al.* 2023; Garcia-Arteaga *et al.* 2024; Liang *et al.* 2024).

3.1. *CRISP-DM framework architecture*

The methodological architecture is based on the CRISP-DM framework, tailored to align with the business and data mining objectives detailed in the introduction section, as depicted in Figure 1. Specifically, the gold rectangles in Figure 1 represent the data understanding and data preparation phases, light green rectangles signify the modelling phase, light turquoise rectangles indicate the evaluation phase, and the lavender rectangles represent the deployments. The primary phase, such as business understanding, has been detailed in the introduction section. This study combined the data understanding and data preparation phases–frequently referred to as data pre-processing in the statistical context–due to the iterative nature of these two processes. During these phases, various Exploratory Data Analysis (EDA) tools and hypothesis tests were utilised to investigate the nonlinear characteristics and assess violations of the pre-defined assumptions in the time series of this study, which is elaborated in the analysis results section. Notably, data cleaning and transformation were not involved in this study.

To achieve the principal business and data mining objectives, secondary structured datasets, such as annual unemployment rates from 1982 to 2020, were sourced from the Department of Statistics Malaysia (DOSM). However, datasets from 1994 and earlier were excluded due to the unrecorded time lag of actual observation in 1994, preserving the dataset's originality without imputing missing values. Consequently, this study's analysis covered 26 years of annual unemployment rates, while unemployment rates for the Territory of Putrajaya were available from 2011 to 2020 (10 observations). However, the data collection methods, such as surveys and censuses for this specific dataset, were not clearly detailed. This lack of detailed metadata limits this study's ability to fully assess the potential impact of these methods on the reliability of the dataset. This study has addressed this limitation in the article by highlighting the importance of understanding data collection processes that evaluate the reliability and quality of input datasets, especially in a predictive modelling context.

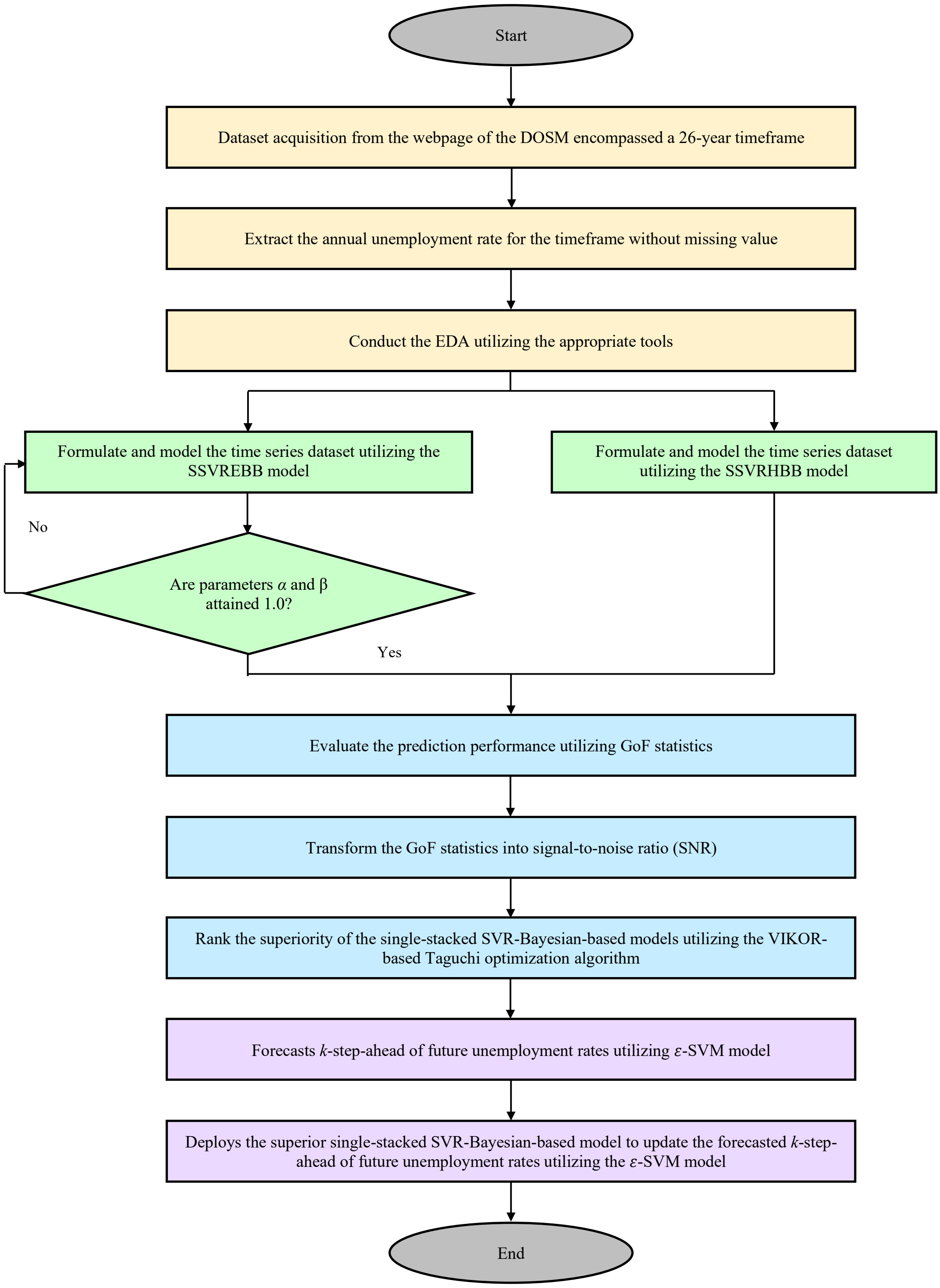


Figure 1: The methodological architecture is based on the CRISP-DM framework

Given the limited sample size and concerns regarding generalisation performance, traditional data-splitting strategies typically utilised in machine learning were avoided (Varoquaux 2018; Xu & Goodacre 2018; Vabalas *et al.* 2019; Hashim *et al.* 2021). Training time series models on small datasets frequently leads to biased or highly uncertain out-of-sample predictions, increasing the risk of underfitting or overfitting. Additionally, the proposed single-stacked SVR-Bayesian-based models effectively integrated all relevant insights into a unified analysis, rendering data-splitting unnecessary (Carriquiry & Pawlovich 2004). Accordingly, this study employed internal validation from a statistical modelling perspective, rather than hold-out cross-validation typically applied in machine learning contexts, aligning with the focus on statistical modelling.

In addition, well-established internal cross-validation methods, such as k-fold, leave-one-out, rolling window, and expanding window approaches, were also not adopted. These approaches introduce inherent stochasticity due to the random partitioning of data, which can disrupt the temporal structure in time series and compromise the reliability of validation results. Furthermore, implementing rolling and expanding window approaches would significantly reduce the effective training data in each fold, potentially causing unstable parameter estimates and decreasing result reliability. This limitation is particularly relevant in the Bayesian framework, where limited data can result in posterior estimates being highly sensitive.

This study further builds upon the conventional stacked ensemble approach in machine learning, where multiple models are trained at the base stage (L0), and their outputs are integrated utilising a meta-model at Stage L1, with appropriate weight assignments. While effective in some contexts, this traditional approach introduces challenges, including determining optimal weight assignments, increasing computational complexity, and reducing interpretability–factors that can impede accurate forecasting of future values. To overcome these limitations, this study developed a simplified single-stacked approach, utilising one model per stage. At Stage L0, this study employed an SVR-based model due to its proven ability to handle nonlinear relationships in a small dataset effectively. At Stage L1, a Bayesian-based model was utilised as the meta-model for its strength in refining predictions by integrating prior knowledge of the new dataset. This streamlined design eliminates the complexities of weight assignment associated with traditional stacked ensembles, enhances computational efficiency, and ensures more interpretable forecasting results. Moreover, this approach aligns with this study's focus on data-limited environments, ensuring that the model remains robust and reliable for actionable insights.

3.2. *Single-stacked SVR-bayesian-based models*

This section provides a concise overview of the SSVREBB and SSVRHBB models, which are single-stacked SVR-Bayesian-based models formulated for this research. The theoretical background of SVR is omitted and acknowledges its well-established status as a semi-parametric statistical learning-based model (Jie *et al.* 2024; Chuan *et al.* 2025). The primary objective of the ε-SVR model in this study is to predict the initial values, which are subsequently updated utilising the proposed single-stacked SVR-Bayesian-based model with a Radial Basis Function (RBF) kernel. The ε-SVR model with an RBF kernel is preferred over the ν-SVR model in this research due to its broader recognition in the literature (Shapi *et al.* 2021; Chuan *et al.* 2025). Both ε-SVR and ν-SVR models are utilised as benchmarks for effectiveness comparison. The key difference between these two models lies in their insensitive loss functions, with ε-SVR utilising an insensitive loss function parameterised by ε, while ν-SVR employs $0 \leq \nu \leq 1$. The regularisation parameter ($\ddot{Y}$) for both models, along with ε; $\varepsilon \geq 0$, is fine-tuned utilising a grid search approach. In this study, the recognised default value of $\varepsilon = 0.1$

is employed for its ability to balance exploration and exploitation across various applications (He 2018; Rätz *et al.* 2019; Chuan *et al.* 2025). Additionally, traditional statistical and AI-based models, such as ARIMA and FeedForward Neural Networks (FFNN) (Glorot & Bengio 2010), were employed as comparison benchmarks to assess the performance of the proposed models under similar controlled environments. Notably, the well-known Recurrent Neural Network (RNN) architecture, such as Long Short-Term Memory (LSTM), is not included as a benchmark, as it poses similar limitations to other AI-based models and shares concepts with FFNN.

While the proposed single-stacked SVR-Bayesian-based models are highly effective in the context of data-limited environments, they may require a more advanced computing environment when applied to larger datasets due to their complexity. Additionally, the proposed models depend on appropriate parameter tuning, which could present a challenge in contexts where computing resources are limited. Despite these potential limitations, the proposed models have demonstrated robustness in handling nonlinear characteristics and maintaining forecast accuracy in real-life applications under data-limited environments. In comparison with traditional statistical and AI-based models, such as ARIMA, SVR-based, and FFNN models, the proposed models offer superior performance, particularly in data-limited environments. Furthermore, the integration of a Taguchi-based VIKOR optimisation algorithm adds an innovative element that enhances model selection, making it more adaptable to complex and data-limited environments. As outlined in the analysis result section, the proposed models outperform these traditional statistical and AI-based models in terms of accuracy and adaptability.

Building on the initial predictions from ε-SVR, the proposed single-stacked SVR-Bayesian-based models, grounded in Bayesian inference, integrate prior inductive reasoning with historical unemployment rates time series datasets, offering greater flexibility than traditional statistical and AI-based models. Particularly, the SSVREBB model utilises a single-level approach, while the SSVRHBB model applies a multi-level structure. The SSVRHBB model is derived from the SSVREBB model under specific assumptions (Carriquiry & Pawlovich 2004). Unlike the classical statistical inference approach utilising Maximum Likelihood (ML) or Ordinary Least Squares (OLS), the SSVRHBB model treats unknown employment rate parameters as random variables, enabling the integration of prior reasoning with the current dataset for more flexible and accurate prediction in data-limited environments.

3.2.1. Theoretical background of the SSVREBB model

Suppose that $\mathbf{Y} = [y_t]_{m\times 1}; t = 1, 2, \dots, m$ represents the total number of annual unemployed labor forces (in thousands), time series at a time lag t, which means the total number of annual unemployed labor forces has a Binomial likelihood function, $y_t \sim \text{Bin}(n_t, \theta_t); 0 \le \theta_t \le 1$, with parameters n_t and θ_t. In specific, n_t and θ_t respectively represent the total number of labor forces and the proportion of unemployment at the time lag t corresponding to the gender for each state or territory. Since the Binomial likelihood function is from the exponential family, the conjugate prior for the Binomial likelihood function exists, resulting in the Beta distribution. $\theta_t \sim \text{Be}(\alpha, \beta)$. By utilising the following Bayes theorem (Eq. 1), tailoring to this research,

$$\Pr(\theta_t | y_t, n_t, \alpha, \beta) = \frac{\Pr(\theta_t) \cdot \Pr(y_t | n_t, \theta_t)}{\int \left(\Pr(\theta_t) \cdot \Pr(y_t | n_t, \theta_t)\right) d\theta_t} \tag{1}$$

where the probability density function of Beta (Be) and the probability mass function of the Binomial distribution (Bin), $\Pr(\theta_t)$ and $\Pr(y_t|n_t,\theta_t)$ can be expressed as Eqs. 2–3, respectively.

$$\Pr(\theta_t) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta_t^{\alpha-1}(1-\theta_t)^{\beta-1} \tag{2}$$

$$\Pr(y_t|n_t,\theta_t) = \binom{n_t}{y_t}\theta_t^{y_t}(1-\theta_t)^{n_t-y_t} \tag{3}$$

which $\Gamma(\cdot)$ is the gamma function. By replacing Eqs. 2–3 with Eq. 1, the following posterior distribution has resulted.

$$\Pr(\theta_t|y_t,n_t,\alpha,\beta) = \frac{\Gamma(n_t+\alpha+\beta)}{\Gamma(y_t+\alpha)\Gamma(n_t-y_t+\beta)}\theta_t^{y_t+\alpha-1}(1-\theta_t)^{n_t-y_t+\beta-1} \tag{4}$$

with $\theta_t|y_t,n_t,\alpha,\beta \sim \text{Be}(y_t+\alpha, n_t-y_t+\beta)$ and the posterior mean, $\text{E}(\theta_t|y_t,n_t,\alpha,\beta)$ and variance, $\text{Var}(\theta_t|y_t,n_t,\alpha,\beta)$ are defined as Eqs. 5–6.

$$\text{E}(\theta_t|y_t,n_t,\alpha,\beta) = \frac{y_t+\alpha}{(y_t+\alpha)+(n_t-y_t+\beta)} \tag{5}$$

$$\text{Var}(\theta_t|y_t,n_t,\alpha,\beta) = \frac{(y_t+\alpha)(n_t-y_t+\beta)}{(n_t+\alpha+\beta)^2(n_t+\alpha+\beta+1)} \tag{6}$$

For visualisation purposes, Figure 2 depicts the computational graphical representation of the SSVREBB model.

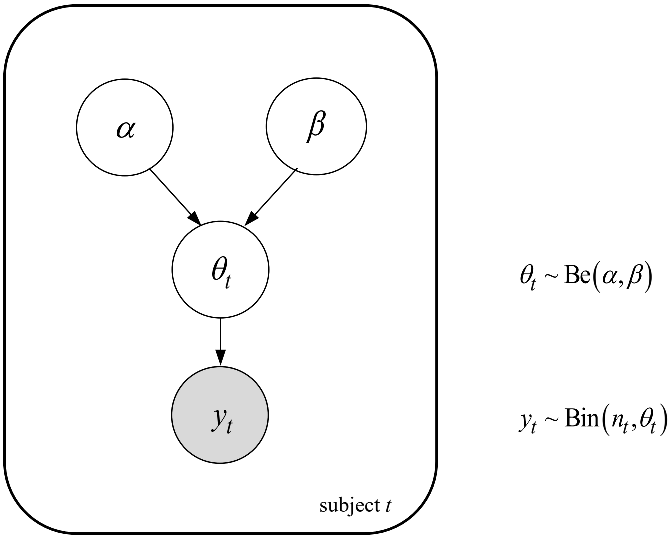


Figure 2: Unveiling the SSVREBB model: A computational visual framework for time series forecasting

where the hyperparameters, α and β, are assumed to be fixed. These hyperparameters for the prior distributions in this research are frequently identical, such that $\alpha = \beta$, and range from 0.1 to 1.0, with increments of 0.1. In other words, this research has employed the weakly informative priors, as well as the lack of prior knowledge about the unknown parameter θ_t. These include Jeffreys' prior, $\theta_t \sim Be(0.5,0.5)$ and uniform prior, $\theta_t \sim Be(1.0,1.0)$.

In this study, the unknown parameter, θ_t was estimated utilising Bayesian statistics via the Markov Chain Monte Carlo (MCMC) simulation based on Gibbs sampling, which is widely employed in Bayesian estimation (Martino *et al.* 2018). The MCMC procedure was implemented with three independent chains ($C = 3$) to facilitate convergence diagnostics. Each chain was run for $I = 100000$ iterations, with the first 50000 iterations discarded as burn-in samples to mitigate the influence of initial values. To reduce autocorrelation among posterior samples, a thinning interval of F=30 was applied, resulting in $1667\left(\left\lfloor\frac{50000}{30}\right\rfloor\right)$ posterior samples per chain, and a total of $4998\left(3\left\lfloor\frac{50000}{30}\right\rfloor\right)$ samples for estimating θ_t. The final estimate θ_t was obtained from the posterior median of these simulated samples.

Meanwhile, convergence of the MCMC simulation was assessed utilising the Gelman-Rubin diagnostic based on the potential scale reduction factor, $\hat{R}$. Values of $\hat{R}$ approaching one $\left(\hat{R} \to 1\right)$ indicate that the chains have likely converged to the targeted posterior distribution. In this study, all estimated parameters produced $\hat{R} \leq 1.001$, confirming convergence. Furthermore, the uncertainty of the estimation was quantified utilising the 95% Highest Density Region (HDR), computed as the interval between the 2.5th and 97.5th percentiles of the posterior samples.

3.2.2. Theoretical Background of the SSVRHBB Model

This research also considered the SSVRHBB model, a full Bayesian model in Bayesian inference. SSVRHBB model performed estimation based on a multi-level model. Literature studies reveal that the full Bayesian model outperforms the empirical Bayesian model in capturing the uncertainty, promoting more causal inferences, and providing greater flexibility in selecting distributions with a small sample size dataset (Persaud *et al.* 2010; Appiah *et al.* 2018; D'Agostino *et al.* 2019). Consequently, the SSVRHBB model, $\Pr(\theta_t, \mu, \tau | y_t, n_t)$ is employed in this research as a comparison, as Figure 3 depicts the computational graphical representation of the SSVRHBB model in predicting the θ_t^*.

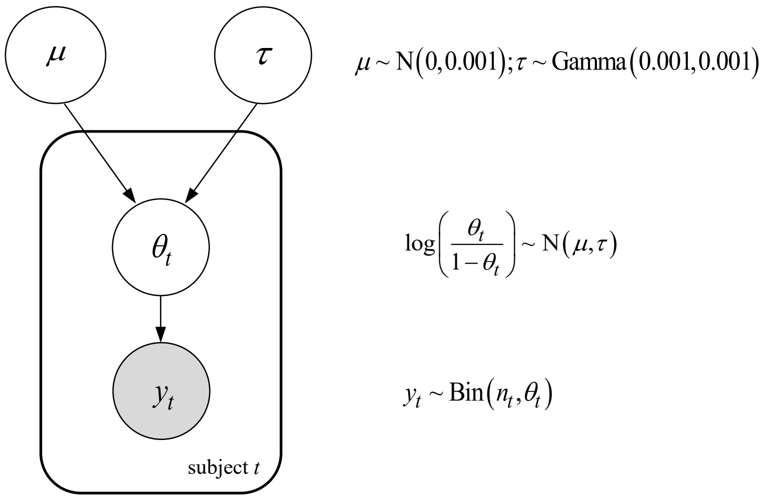


Figure 3: Unveiling the SSVRHBB model: A computational visual framework for time series forecasting

Based on Figure 3, $y_t; t = 1, 2, \ldots, m$ depicts the collection of observed random variables for the total number of annual unemployed labor forces corresponding to the gender in each state or territory with a Binomial distribution, $y_t \sim \mathrm{Bin}(n_t, \theta_t)$. In statistical theory, the log-odds of θ_t, $\log\left(\frac{\theta_t}{1-\theta_t}\right)$ is approximately Fisher's z or the Normal distribution, $\mathrm{N}(\mu, \tau)$ with mean μ

and variance τ when m is sufficiently large. Since it was more convenient working with the Normal distribution, therefore $\log\left(\frac{\theta_t}{1-\theta_t}\right) \approx N(\mu, \tau)$ has been employed as the prior with two unknown hyperparameters, μ and τ, and assumed to be random. The θ_t will be identical when $\tau \to 0$. This also leads to y_t is pooling across the years to learn about a single population. In particular, the hyperparameters μ and τ are shared over m years. From the practical perspective, μ and τ characterised the location and the scale of the annual unemployment rates of each state or territory in Malaysia. Moreover, this research has employed weakly informative hyperprior distributions, $\mu \sim N(0,0.001)$ and $\tau \sim \text{Gamma}(0.001,0.001)$, where Gamma represents the Gamma distribution. This is due to there being little prior knowledge about the hyperparameters μ and τ. To estimate the $\hat{\theta}_t^*$ and its 95% HDR, the SSVRHBB model utilised a simulation mechanism similar to the SSVREBB model. Based on the Bayesian statistical inference, the SSVRHBB model can be mitigated into the SSVREBB model when the hyperparameters μ and τ are assumed to be fixed.

3.3. *Goodness-of-fits (GoF) statistics*

This research utilised the Deviance Information Criteria (DIC) to compare predictive loss and select superior single-stacked SVR-Bayesian-based models. In statistics, DIC is a hierarchical generalisation of the Akaike Information Criterion (AIC), integrating deviance-based complexity measurement and GoF statistics. This metric is utilised to monitor the relative fit of the SSVREBB and SSVRHBB models in MCMC. Moreover, several well-known GoF statistics, such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) (Peláez 2006; Sharma & Singh 2016; Ramli *et al.* 2018; Katris 2020; Davidescu *et al.* 2021) were employed to assess the discrepancy between observed and predicted annual unemployment rates corresponding to the gender for each state and territory across the regions. The prediction uncertainty of θ_t, and δ, was also considered as one of the GoF statistics. In mathematics, these GoF statistics can be expressed as Eqs. 7–11, respectively.

$$\text{DIC} = 2\bar{D}(\boldsymbol{\theta}) - D(\bar{\boldsymbol{\theta}}) \tag{7}$$

$$\text{MAPE} = \frac{100}{m}\sum_{t=1}^{m}\left|\frac{\theta_t - \hat{\theta}_t^*}{\hat{\theta}_t^*}\right| \tag{8}$$

$$\text{MAE} = \frac{1}{m}\sum_{t=1}^{m}\left|\theta_t - \hat{\theta}_t^*\right| \tag{9}$$

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{t=1}^{m}\left(\theta_t - \hat{\theta}_t^*\right)^2} \tag{10}$$

$$\delta = \text{U}_{\text{HDR}} - \text{L}_{\text{HDR}} \tag{11}$$

where L_{HDR} and U_{HDR} are the lower and upper bounds for the 95% HDR of $\hat{\theta}_t^*$. Meanwhile, $\bar{D}(\boldsymbol{\theta})$ and $D(\bar{\boldsymbol{\theta}})$ represent the posterior mean of the deviance and the deviance at the posterior mean $\bar{\boldsymbol{\theta}}$, respectively. The mathematical equations for the $\bar{D}(\boldsymbol{\theta})$, and $D(\bar{\boldsymbol{\theta}})$ of the SSVREBB model can be defined as Eqs. 12–13, respectively.

$$\bar{D}(\boldsymbol{\theta}) = \text{E}_{\theta_t|y_t,n_t,\alpha,\beta}\left(-2\log\left(\Pr(y_t|n_t,\theta_t)\right)\right) \tag{12}$$

$$D(\bar{\boldsymbol{\theta}}) = D\left(\text{E}(\theta_t|y_t,n_t,\alpha,\beta)\right) \tag{13}$$

Meanwhile, $\bar{D}(\boldsymbol{\theta})$ and $D(\bar{\boldsymbol{\theta}})$ for the SSVRHBB model yielded by replacing the term of $\theta_t|y_t,n_t,\alpha,\beta$ in Eq. 12 and Eq. 13 with $\theta_t,\mu,\tau|y_t,n_t$. The observed and predicted annual unemployment rates are considered well-fitted when the DIC, MAPE, MAE, and RMSE, and δ approach zero. The non-parametric multivariate analysis of variance, known as the multivariate Kruskal-Wallis test (MKW), is employed to identify statistically significant differences in the GoF statistics corresponding to gender across regions, states, and territories. The MKW test was applied because the generalised Shapiro-Wilk test indicated that both datasets are not multivariate normally distributed (Male: test statistic = 0.6865, p-value < 2.2E-16; Female: test statistic = 0.7086, p-value < 2.2E-16). Furthermore, the MKW test evidenced statistically significant differences among the GoF statistics corresponding to gender (Male: test statistic = 238.5251, p-value = 2.2121E-26; Female: test statistic = 270.3915, p-value = 5.2444E-32).

3.4. *VIKOR-based Taguchi optimisation algorithm*

Taguchi's robust design is a significant technique utilised for optimising product or process performance based on SNR, which aids in monitoring performance effects by minimising variability around the targeted value. Generally, SNR can be classified into three cases: larger is a better SNR, nominal is the best SNR, and lower is a better SNR (Menard *et al.* 2020). In this research, a lower a better SNR is preferred as the principal objective is to minimise the GoF statistics as Eqs. 7–11. Hence, the GoF statistics are transformed into the SNR (in decibels) by applying Eq. 14.

$$a_{ij} = -10\log\left(\zeta_{ij}^2\right); i, (j) = 1, 2, \dots, g, (h) \tag{14}$$

where ζ_{ij} represents the ith GoF statistics for the jth single-stacked SVR-Bayesian-based model.

Suppose that $\mathbf{A} = \left[a_{ij}\right]_{g\times h}$ is the normalised matrix resulting from the collection of the a_{ij}, which comprises g transformed GoF statistics, and h single-stacked SVR-Bayesian-based models. Therefore, the superiority of these single-stacked SVR-Bayesian-based models taken into account in this research is ranked in ascending order of VIKOR scores, η_j (Bathaei *et al.* 2019; Chuan *et al.* 2020) given as Eq. 15.

$$\eta_j = 0.5\left(\frac{\kappa_j - \min\limits_j(\kappa_j)}{\max\limits_j(\kappa_j) - \min\limits_j(\kappa_j)} + \frac{\kappa'_j - \min\limits_j(\kappa'_j)}{\max\limits_j(\kappa'_j) - \min\limits_j(\kappa'_j)}\right) \tag{15}$$

where the utility, κ_j and the regret κ'_j measures for the single-stacked SVR-Bayesian-based models with criterion functions, $\Psi_j^+ = \max\limits_j a_{ij}$ and $\Psi_j^- = \min\limits_j a_{ij}$ can be expressed as Eqs. 16–17.

$$\kappa_j = \sum_{i=1}^{g} \frac{\omega_i\Psi_i^+ - \omega_i a_{ij}}{\Psi_j^+ - \Psi_j^-} \tag{16}$$

$$\kappa'_j = \max_i\left(\frac{\omega_i\Psi_i^+ - \omega_i a_{ij}}{\Psi_j^+ - \Psi_j^-}\right) \tag{17}$$

which is the weighted function, $\omega_i = \frac{\frac{1}{h-1}\sum_{j=1}^{h}\left(a_{ij} - \bar{a}_{ij}\right)^2}{\sum_{i=1}^{g}\left(\frac{1}{h-1}\sum_{j=1}^{h}\left(a_{ij} - \bar{a}_{ij}\right)^2\right)}$ with $\bar{a}_{ij} = \frac{1}{h}\sum_{j=1}^{h} a_{ij}$ and $\sum_{i=1}^{g}\omega_i = 1$.

The VIKOR-based Taguchi optimisation algorithm is employed in this research due to the lack of congruence among the GoF statistics. Its effectiveness is vital for achieving the optimal decision. The superiority of the three selected single-stacked SVR-Bayesian-based models is further verified by comparing them with previously proposed traditional Box-Jenkins, semi-parametric, and parametric models. These include ARIMA, ε-SVR, ν-SVR, and FFNN. The arithmetic average of GoF statistics is utilised to rank these models, as there is no lack of congruence among these statistics. In this stage, the criteria such as DIC and δ are not applicable to traditional Box-Jenkins, semi-parametric, and parametric models and have been eliminated. This is because these models do not generate the posterior distribution needed for DIC, and δ calculation.

4. Analysis Results and Discussion

This research exclusively utilised R Version 4.0.4 (2021-02-15) statistical software for statistical analysis, conducted within a mid-range computing environment (Processor: Intel® Core™ i5-10210U CPU @ 1.60GHz; RAM: 4 GB). The source code and scripts developed for this study are confidential. Various EDA techniques and statistical hypotheses tests were employed to profile yearly unemployment rates based on genders (male and female), regions (Northern, East Coast, Central, Southern, Sabah, and Sarawak), states (Kedah (KDH), Perak (PRK), Perlis (PLS), Pulau Pinang (PNG), Kelantan (KTN), Pahang (PHG), Terengganu (TRG), Selangor (SGR), Johor (JHR), Melaka (MLK), Negeri Sembilan (NSN), Sabah (SBH), and Sarawak (SWK)), and territory (Kuala Lumpur (KUL), Putrajaya (PJY), and Labuan (LBN)), as well as to assess the nonlinear relationships that are useful for evaluating the sensitivity of the proposed single-stacked SVR-Bayesian-based models compared to the benchmarks. Particularly, EDA tools, including boxplots, medians, interquartile ranges (*IQR*), skewness, and kurtosis, were utilised to characterise the central tendency and spread of the dataset, which is mostly non-normally distributed with the presence of extreme values. Medians and *IQR* were utilised instead of arithmetic means and variance as robust numerical summaries for non-normal datasets with extreme values. Despite the robustness of medians and *IQR* in summarising non-normal datasets, this approach has typical limitations, as it is less sensitive to the specific magnitudes of extreme values. This may limit the interpretability of cross-state comparisons, particularly when the sample size is small. However, in this study, the impact of this limitation is mitigated because the datasets across regions, states, and territories cover a consistent time period, allowing meaningful descriptive comparisons even in a data-limited environment. Meanwhile, boxplots, skewness, and kurtosis were also utilised in assessing the dataset's normality, avoiding hypothesis testing due to the small sample size’s impact on the statistical test power.

For time series analysis, various statistical hypothesis tests were conducted to investigate key characteristics, including stationarity, nonlinearity, monotonic trend, and seasonality, which are typically required for the development of a traditional ARIMA model and for evaluating model sensitivity. However, these tests do not directly affect semi-parametric, parametric statistical learning-based, and single-stacked SVR-Bayesian-based models employed in this study. Specifically, the Kwiatkowski-Philips-Schmidt-Shin (KPSS) test, Keenan test, Mann-Kendall test, Webel-Ollech overall seasonality (WO) test, and Portmanteau-Q test were utilised to assess stationarity, linearity, monotonic trend, seasonality, and autoregressive conditional heteroscedasticity (ARCH) effects, respectively. Due to the limited sample size, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were not applied for the unit root test. In addition, formal diagnostic checks for the traditional ARIMA model were not conducted in this study, as the limited sample size makes it challenging to reliably satisfy the underlying assumptions of the model, particularly the white noise requirement. It has been noted in the literature that ARIMA models generally require a sufficiently large sample size to ensure meaningful diagnostic validation.

4.1. *Impactful models for male unemployment rates*

In Figure 4, the five-number summary of annual unemployment rates for the male labor market in various regions conveyed asymmetrical distributions. This is evident as the median does not align with the middle of the minimum and maximum values. The skewness and kurtosis values in Table 1 also supported this analysis result, except for SBH, which exhibited an opposite skewness due to extreme values and non-normality in the datasets. For PLS, PNG, PRK, and KUL, the distributions are approximately symmetrical, with minimal influence from extreme values. However, a more detailed data exploration utilising central tendency measures revealed slight influences.

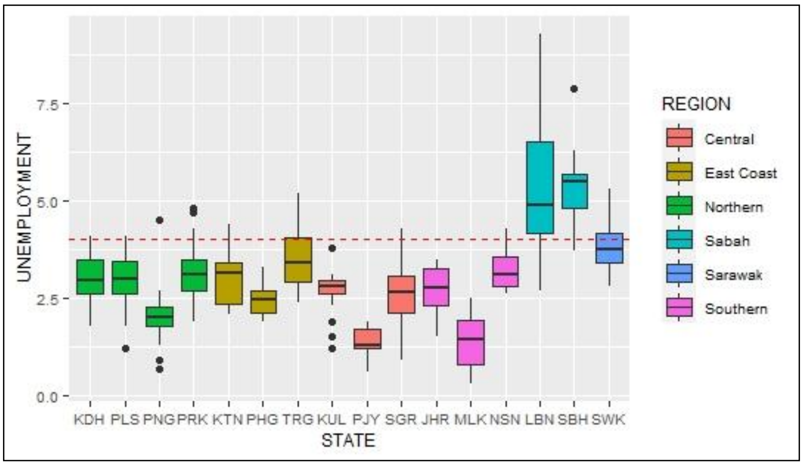


Figure 4: Boxplot of annual unemployment rates for males across regions

The exceptionally high unemployment rates in PNG (4.50%), KUL (3.80%), SBH (7.90%), and PRK (4.30%) were primarily due to the massive impact of the COVID-19 pandemic, resulting in significant job losses in these states and territories in 2020. Additionally, PRK experienced a high rate in 1999 (4.80%) and 2003 (4.70%), which could be attributed to the recession of Malaysia's financial crisis in 1997-1998, the Nipah virus Outbreak in 1998-1999, and the Severe Acute Respiratory Syndrome (SARS) in 2002-2003. These disasters impacted the state's principal economic activity in the services, agriculture, and manufacturing sectors. Despite facing the COVID-19 pandemic, PRK did not exhibit an extremely high unemployment rate in 2020.

For SBH, the annual unemployment rates from 1995 to 2020 consistently surpassed the frictional unemployment rates on average, as shown in Figure 1 and Table 1. This could be attributed to various natural and human-made disasters, including Tropical Storm Greg in 1996, El Niño-induced severe drought in 1997, Nipah Virus Outbreak in 1999, a landslide in 1999, SARS in 2002-2003, Avian Influenza in 2003-2007, La Niña-induced floods in 2011 and 2012, an earthquake in 2015, and the COVID-19 pandemic in 2020. These disasters led to losses in tourism revenue, agriculture revenue, forestry revenue, and livelihoods, as well as damage to infrastructure, property, and crops, resulting in increased unemployment rates. These calamities also impacted SBH's principal economic activities in the service and agriculture sectors (Kang *et al.* 2020).

Table 1: Statistical summaries and evidence of principal characteristics in annual male unemployment time series datasets

Region	State	Numerical Measures				Characteristic			
		Median	IQR	Skewness	Kurtosis	Stationary (*p*-value)	Nonlinear (*p*-value)	Trend (*p*-value)	Seasonal (*p*-value^1; *p*-value^2)
Northern	KDH	2.9500	0.8500	-0.1824	-0.8786	Yes (≥0.1000)	No (0.0984)	No (0.7571)	No (1.00001;0.6624^2)
	PLS	3.0000	0.8500	-0.5472	0.0920	Yes (≥0.1000)	No (0.8414)	No (0.1157)	No (1.00001;0.9590^2)
	PNG	2.0000	0.4750	1.2803	4.1022	Yes (≥0.1000)	No (0.7198)	No (0.5799)	No (1.0000^1;0.4727^2)
	PRK	3.1000	0.7750	0.5602	0.1066	Yes (≥0.1000)	No (0.6540)	No (0.1382)	No (1.0000^1;0.9590^2)
East Coast	KTN	3.1500	1.0500	0.2531	-0.7583	Yes (≥0.1000)	No (0.0783)	No (0.4919)	No (1.0000^1;0.1437^2)
	PHG	2.4500	0.5500	0.1869	-0.6084	Yes (≥0.1000)	No (0.5828)	No (0.1754)	**Yes (0.0017^1;0.0164^2)**
	TRG	3.4000	1.1500	0.4218	-0.8904	Yes (≥0.1000)	**Yes (0.0484)**	No (0.0546)	No (0.2118^1;0.5903^2)
Central	KUL	2.8000	0.3750	-1.0011	1.4820	**No (0.0249)**	No (0.8450)	**Yes (0.0047)**	No (1.0000^1;0.6436^2)
	PJY*	1.3000	0.5250	-0.2876	-0.9113	Yes (≥0.1000)	No (0.8642)	No (0.6508)	No (1.0000^1;0.2463^2)
	SGR	2.6500	0.9500	-0.1418	0.0045	Yes (≥0.1000)	No (0.3276)	**Yes (0.0491)**	No (1.0000^1;0.9183^2)
Southern	JHR	2.7500	0.9500	-0.4259	-0.9023	Yes (≥0.1000)	No (0.6463)	**Yes (0.0465)**	No (0.8921^1;0.2931^2)
	MLK	1.4500	1.1500	0.1236	-1.4732	**No (0.0174)**	No (0.1580)	**Yes (0.0024)**	No (1.0000^1;0.3428^2)
	NSN	3.1000	0.7750	0.5073	-0.8195	Yes (≥0.1000)	No (0.5407)	**Yes (0.0122)**	No (0.4552^1;0.6062^2)
Sabah	LBN	4.9000	2.3500	0.5700	-0.8832	**No (0.0173)**	No (0.4393)	**Yes (0.0002)**	No (1.0000^1;0.1303^2)
	SBH	5.5000	0.8750	**0.8075**	**2.2739**	Yes (≥0.1000)	No (0.6989)	No (0.2072)	No (1.0000^1;0.4266^2)
Sarawak	SWK	3.7500	0.7750	0.3617	-0.3021	Yes (≥0.1000)	No (0.5666)	No (0.1063)	No (1.0000^1;0.9387^2)

The aforementioned statement can be supported by previous studies. Specifically, numerous macroeconomic studies in both developing and developed nations, including the recession of financial crisis (Ariff & Abubakar 1999), Avian influenza (Ozbay *et al.* 2021), floods, droughts, storms, and earthquakes (Panwar & Sen 2019), Nipah virus Outbreak (Lam 2003), MERS (Lee & Cho 2016; Ozbay *et al.* 2021) and SARS (Lee & Warner 2005, 2006; Lee & Cho 2016; Ozbay *et al.* 2021), COVID-19 pandemic (Hashim *et al.* 2021; Muthukumar & Salini 2021; Ozbay *et al.* 2021) have established a relationship between natural disasters and high unemployment rates.

Statistical hypotheses were tested to investigate the principal characteristics of the annual unemployment rate time series dataset, as shown in Table 1. The goal of this analysis was to develop a superior ARIMA model and to assess the dynamic effectiveness of the SVR-based and the proposed single-stacked SVR-Bayesian-based models across various nonlinear scenarios in comparison to the ARIMA model. Meanwhile, the prediction performances and ranking of these models are presented in Table 2. The KPSS test revealed non-stationarity in KUL, MLK, and LBN, necessitating first-order differencing utilising ARIMA models (Table 2). Differencing aided detrend datasets with visible monotonic trends. Autoregressive addressed specific features, eliminating significant trends in SGR and JHR, while rectifying TRG's quadratic form indicated by the Keenan test.

Table 2: Performance of models for the male labor market

Region	State	Model	GoF statistics			Rank
			MAPE	MAE	RMSE	
Northern	KDH	ARIMA(0,0,0)	18.3073	0.5000	0.5993	7
		ε-SVR	15.7427	0.3746	0.4737	5
		υ-SVR	12.8669	0.3568	0.4461	3
		FFNN	14.7249	0.4147	0.5183	4
		$\mathbf{M_9^P}$	**3.6564**	**0.1027**	**0.1095**	**1**
		M_{10}^P	4.4909	0.1262	0.1312	2
		M_{11}^P	17.0722	0.4695	0.5638	6
	PRK	ARIMA(0,0,0)	16.9304	0.5142	0.6837	7
		ε-SVR	14.7351	0.4390	0.6047	3
		υ-SVR	14.8476	0.4506	0.6203	4
		FFNN	15.6822	0.4756	0.6029	5
		$\mathbf{M_9^P}$	**2.8259**	**0.0878**	**0.0933**	**1**
		M_{10}^P	3.4746	0.1082	0.1142	2
		M_{11}^P	15.3203	0.4711	0.6322	6
	PLS	ARIMA(1,0,0)	14.8541	0.3836	0.5368	6
		ε-SVR	11.7170	0.3439	0.5131	4
		υ-SVR	15.5862	0.4120	0.4926	7
		FFNN	12.5248	0.3662	0.4611	5
		M_2^P	7.4963	0.1975	0.2113	3
		$\mathbf{M_3^P}$	**2.3054**	**0.0654**	**0.0796**	**1**
		M_4^P	5.0783	0.1366	0.1571	2
	PNG	ARIMA(1,0,0)	22.4168	0.3968	0.6208	5
		ε-SVR	21.7134	0.3814	0.5848	3
		υ-SVR	22.7959	0.3856	0.5879	6
		FFNN	21.8773	0.3876	0.5721	4
		$\mathbf{M_9^P}$	**7.8066**	**0.1344**	**0.1384**	**1**
		M_{10}^P	8.8707	0.1532	0.1574	2
		M_{11}^P	25.9557	0.4078	0.6248	7
East Coast	KTN	ARIMA(1,0,0)	14.2082	0.4170	0.5327	6
		ε-SVR	11.0691	0.3215	0.4582	3
		υ-SVR	11.5044	0.3453	0.4689	4
		FFNN	11.8949	0.3469	0.4812	5
		$\mathbf{M_9^P}$	**5.5923**	**0.1631**	**0.1681**	**1**
		M_{10}^P	6.7265	0.1952	0.2007	2
		M_{11}^P	17.9525	0.5085	0.6036	7
	PHG	ARIMA(0,0,0)	12.3932	0.2923	0.3520	7
		ε-SVR	8.6660	0.2050	0.2637	5
		υ-SVR	9.4864	0.2213	0.2701	6
		FFNN	6.7030	0.1608	0.1991	3
		$\mathbf{M_8^P}$	**5.0578**	**0.1216**	**0.1280**	**1**
		M_9^P	6.0844	0.1468	0.1536	2

Table 2 (Continued)

		M_{10}^P	6.9542	0.1669	0.1721	4
	TRG	ARIMA(1,0,0)	14.0070	0.4666	0.6029	7
		ε-SVR	10.5667	0.3713	0.4710	4
		υ-SVR	11.4533	0.3921	0.4704	5
		FFNN	12.8076	0.4207	0.5109	6
		M_1^P	2.6897	0.0864	0.0945	2
		$\mathbf{M_5^P}$	**1.9016**	**0.0634**	**0.0714**	**1**
		M_6^P	3.2405	0.1063	0.1132	3
Central	KUL	ARIMA(0,1,0)	13.5143	0.3347	0.4562	6
		ε-SVR	11.1763	0.2456	0.3684	4
		υ-SVR	11.4120	0.2601	0.3679	5
		FFNN	9.4683	0.2298	0.3243	3
		$\mathbf{M_9^P}$	**4.7969**	**0.1181**	**0.1246**	**1**
		M_{10}^P	5.7241	0.1422	0.1474	2
		M_{11}^P	16.3251	0.3411	0.4949	7
	PJY*	ARIMA(0,0,0)	27.6321	0.3040	0.3743	3
		ε-SVR	**19.8706**	**0.1820**	**0.2810**	**1**
		υ-SVR	23.8900	0.2342	0.3056	2
		FFNN	28.2266	0.3000	0.3813	4
		M_8^P	203.7064	2.4933	2.4998	5
		M_9^P	238.2373	2.9281	2.9349	6
		M_{10}^P	273.5965	3.3634	3.3665	7
	SGR	ARIMA(1,0,0)	18.2565	0.3902	0.5373	6
		ε-SVR	14.6774	0.2911	0.4501	4
		υ-SVR	15.1656	0.3131	0.4601	5
		FFNN	18.3408	0.3884	0.4774	7
		$\mathbf{M_9^P}$	**1.8916**	**0.0404**	**0.0481**	**1**
		M_{10}^P	2.2256	0.0466	0.0552	2
		M_{11}^P	12.8525	0.2320	0.3142	3
Southern	JHR	ARIMA(1,0,0)	18.1829	0.4505	0.5207	7
		ε-SVR	15.7427	0.3746	0.4737	3
		υ-SVR	17.2895	0.4050	0.4800	5
		FFNN	16.3507	0.4126	0.4800	4
		$\mathbf{M_9^P}$	**2.3475**	**0.0582**	**0.0657**	**1**
		M_{10}^P	2.5783	0.0646	0.0715	2
		M_{11}^P	18.1095	0.4314	0.5090	6
	MLK	ARIMA(0,1,0)	39.4324	0.4655	0.6496	6
		ε-SVR	27.2022	0.3321	0.4678	4
		υ-SVR	30.7848	0.3377	0.4427	5
		FFNN	40.8358	0.4190	0.5469	7
		M_2^P	6.4266	0.0642	0.0729	2
		$\mathbf{M_3^P}$	**3.2231**	**0.0330**	**0.0399**	**1**
		M_5^P	8.1156	0.0911	0.1015	3
	NSN	ARIMA(0,0,0)	12.2685	0.3935	0.4529	7
		ε-SVR	7.1093	0.2439	0.3769	2
		υ-SVR	7.4023	0.2527	0.3751	4
		FFNN	9.8573	0.3208	0.4071	5
		$\mathbf{M_9^P}$	**6.3692**	**0.2032**	**0.2113**	**1**
		M_{10}^P	7.4346	0.2372	0.2445	3
		M_{11}^P	11.6002	0.3785	0.4397	6
Sabah	LBN	ARIMA(0,1,1)	24.8234	1.2430	1.6894	7
		ε-SVR	20.1912	0.9599	1.3218	4
		υ-SVR	20.1695	1.0134	1.3474	5
		FFNN	20.6454	0.9245	1.2311	6
		M_2^P	9.1423	0.4322	0.4461	3
		$\mathbf{M_3^P}$	**2.0776**	**0.0960**	**0.1245**	**1**

Table 2 (Continued)

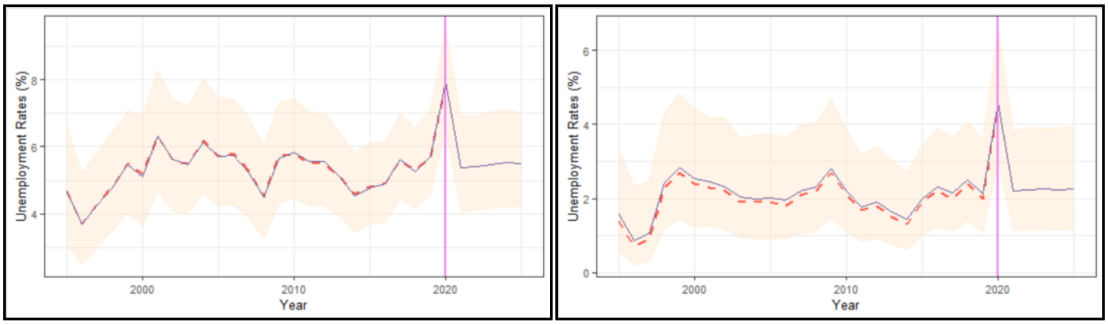
		M_4^P	5.4489	0.2500	0.2807	2
	SBH	ARIMA(1,0,0)	8.8238	0.4770	0.6784	6
		ε-SVR	7.3669	0.3963	0.6248	4
		υ-SVR	7.7137	0.4164	0.6161	5
		FFNN	8.9637	0.4831	0.6730	7
		$\mathbf{M_2^P}$	**0.5548**	**0.0297**	**0.0381**	**1**
		M_3^P	0.5857	0.0313	0.0394	3
		M_4^P	0.5700	0.0309	0.0350	2
Sarawak	SWK	ARIMA(1,0,0)	10.4822	0.3893	0.5179	5
		ε-SVR	8.4142	0.3317	0.4664	3
		υ-SVR	8.5332	0.3303	0.4540	4
		FFNN	10.9476	0.4079	0.5079	6
		$\mathbf{M_9^P}$	**2.1194**	**0.0771**	**0.0859**	**1**
		M_{10}^P	2.6643	0.0976	0.1065	2
		M_{11}^P	11.7569	0.4364	0.5474	7

***Note:** SSVREBB models: $Pr(\theta_t|y_t, n_t, \alpha, \beta)$, $\mathbf{M_1^P}$: $\alpha = \beta = 0.1$, $\mathbf{M_2^P}$: $\alpha = \beta = 0.2$, $\mathbf{M_3^P}$: $\alpha = \beta = 0.3$, $\mathbf{M_4^P}$: $\alpha = \beta = 0.4$, $\mathbf{M_5^P}$: $\alpha = \beta = 0.5$, $\mathbf{M_6^P}$: $\alpha = \beta = 0.6$, $\mathbf{M_8^P}$: $\alpha = \beta = 0.8$, $\mathbf{M_9^P}$: $\alpha = \beta = 0.9$, $\mathbf{M_{10}^P}$: $\alpha = \beta = 0.3$; SSVRHBB model: $\mathbf{M_{11}^P}$: $\Pr(\theta_t, \mu, \tau|y_t, n_t)$

In simple terms, these results implied that the proposed SSVREBB models are more dynamic and robust in fitting the limited male unemployment rates time series datasets, which comprise a variety of nonlinear characteristics, and that they violate the pre-defined assumptions of traditional statistical models in the context of stationary, nonlinearity, trend, and seasonality across regions and Malaysia's states, as shown in Table 1. Additionally, these findings consolidate the limitation discussed in the introduction section, which points out that traditional statistical and AI-based models struggle to perform well in limited datasets with fewer than 30 observations. Data-splitting strategies, utilising pre-defined training-to-test ratios such as 60:40, 70:30, 80:20, and 90:10, can further diminish predictive accuracy for these models. Specifically, utilising fewer observations to train these models can lead to overfitting and decreased predictive accuracy. However, the results demonstrate that different values for α and β are required to optimise predictive accuracy for time series datasets exhibiting different characteristics.

To forecast the k-step-ahead annual unemployment rate, this article suggests predicting the values y_{t+k} and n_{t+k} utilising the ε-SVR model for initial prediction, followed by updating with the superior SSVREBB model. The resulting $\hat{\theta}^*_{t+k}$ represents the forecasted future annual unemployment rates. Figure 5 illustrates the examples of forecasted 5-year unemployment rates for SBH and PNG, utilising the M_2^P and M_9^P models, which had the lowest and highest average of GoF statistics (MAPE, MAE, and RMSE) among the top-ranked SSVREBB models across different regions, states, and federal territories. The observed and predicted annual unemployment rates were represented by red dashed and navy-blue lines in Figure 5, with the shaded region representing the 95% HDR of the predicted rates. The forecasted results for SBH, as shown in Figure 5(a), are aligned with the actual observed unemployment trends. For instance, the Department of Statistics Malaysia (n.d.) reported that male unemployment rates in SBH decreased from 7.9% in 2020 to 7.3% in 2021, continuing to drop to 6.6% in 2022. These trends are parallel with the forecasted downward movement, suggesting the SSVREBB model's accuracy when effective employment of 27 initiatives, including *Program Penjana Kerjaya* (Ruzki & Sulaiman 2021), and Malaysia Short Term Employment Program (MySTEP) (Azaman 2021), are implemented. However, the forecasted unemployment in 2021 deviated from the actual observation of 4.6%, primarily due to unexpected economic impacts from the

COVID-19 pandemic. Nearly 50 factories in PNG temporarily closed for the first three months of 2021, which impacted employment, particularly in the manufacturing sector (Leng 2021). Consequently, the forecasted rate was unable to fully account for these unprecedented disruptions, as PNG experienced a decrease in male unemployment from 4.5% in 2020 to 3.2% in 2022.



(a) (b)

Figure 5: Examples of forecasted 5-year unemployment rates (navy-blue lines after 2020) for (a) SBH and (b) PNG, respectively

4.2. *Impactful Models for Female Unemployment Rates*

Figure 6 depicts that the number of states with female unemployment rates exceeding the frictional unemployment rate on average has increased. This is supported by the median unemployment rates in Table 3, with PRK (4.20%), LBN (5.05%), SBH (5.75%), and SWK (4.30%) having rates higher than 4.00%. Most time series were asymmetrically distributed, as illustrated in Figure 6, and characterised in Table 3 for skewness and kurtosis. Similar to the male unemployment rates, there was a contradiction between the shape of the distribution characterised by the boxplot and the skewness and kurtosis values for KDH and NSN. The utilisation of arithmetic means to compute skewness is not robust in the presence of extreme values. Additionally, extreme annual unemployment rates were observed in KDH, PLS, PHG, TRG, KUL, SGR, MLK, and NSN in 2009 (4.90%), 1998 (6.00%), 1995 (5.50%), 1995 (7.40%), 2020 (4.20%), 2020 (4.40%), 2002 (4.10%), and 2006. (4.70%), respectively. These extreme rates could be attributed to disasters such as floods, financial crises, the COVID-19 pandemic, SARS, and Avian influenza, as discussed in Section 3.1.

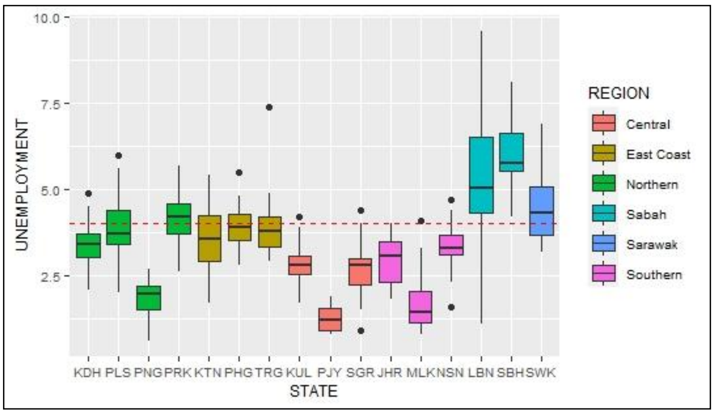


Figure 6: Boxplot of annual unemployment rates for females across regions

Table 3: Statistical summaries and evidence of principal characteristics in annual female unemployment time series datasets

Region	State	Numerical Measures				Characteristic			
		Median	IQR	Skewness	Kurtosis	Stationary (*p*-value)	Nonlinear (*p*-value)	Trend (*p*-value)	Seasonal (*p*-value[1]; *p*-value[2])
Northern	KDH	3.4000	0.6750	0.1830	-0.1480	Yes (≥0.1000)	No (0.6475)	No (0.6585)	No (0.6806[1];0.9183[2])
	PLS	3.7000	1.0000	0.3965	-0.5158	Yes (≥0.1000)	No (0.0579)	No (0.1218)	No (1.0000[1];0.8775[2])
	PNG	1.9500	0.6750	-0.6646	0.1703	Yes (≥0.1000)	**NA**	No (0.3079)	No (1.0000[1];0.6993[2])
	PRK	4.2000	0.8500	-0.0207	0.3359	Yes (≥0.1000)	No (0.3741)	No (0.2502)	No (1.0000[1];0.9590[2])
East Coast	KTN	3.5500	1.3250	0.1859	-0.6223	Yes (≥0.1000)	No (0.5879)	No (0.2004)	No (1.0000[1];0.9795[2])
	PHG	3.9000	0.7500	0.2905	0.1100	Yes (≥0.1000)	**Yes (0.0053)**	No (0.3082)	No (1.0000[1];0.5367[2])
	TRG	3.8000	0.8750	2.0564	5.6514	Yes (≥0.1000)	**Yes (0.0000)**	No (0.9647)	No (0.8921[1];0.2931[2])
Central	KUL	2.8000	0.5500	0.1632	-0.5367	**No (0.0244)**	No (0.2075)	**Yes (0.0074)**	No (1.0000[1];0.5554[2])
	PJY*	1.2000	0.6250	0.3354	-1.5164	Yes (0.0839)	No (0.3442)	No (0.2793)	No (1.0000[1];0.5993[2])
	SGR	2.8000	0.7500	-0.1282	-0.1851	**No (0.0202)**	No (0.2340)	**Yes (0.0003)**	No (1.0000[1];0.3164[2])
Southern	JHR	3.0500	1.1750	-0.0193	-1.4286	Yes (≥0.1000)	No (0.5195)	**Yes (0.0240)**	No (0.5959[1];0.1303[2])
	MLK	1.4500	0.9250	1.2423	0.8204	Yes (≥0.1000)	No (0.5312)	No (0.1218)	No (1.0000[1];0.1062[2])
	NSN	3.3000	0.5750	-0.3832	0.6740	Yes (≥0.1000)	No (0.1426)	No (0.8942)	No (1.0000[1];0.5726[2])
Sabah	LBN	5.0500	2.2000	0.2650	-0.2798	Yes (≥0.1000)	**Yes (0.0460)**	No (0.6430)	No (1.0000[1];0.3975[2])
	SBH	5.7500	1.1000	0.4887	-0.5671	Yes (≥0.1000)	No (0.0965)	No (0.7401)	No (1.0000[1];0.9590[2])
Sarawak	SWK	4.3000	1.4000	0.7078	0.0234	**No (≥0.0100)**	No (0.1632)	**Yes (0.0000)**	No (1.0000[1];0.3692[2])

The descriptive summary in Table 1 and Table 3 revealed that the female labor force's annual unemployment rates were statistically significantly higher in 8 out of 16 (50.00%) states and territories compared to the male labor forces tested utilising the Wilcoxon rank-sum test (*p*-value for KDH: 0.0136, PLS: 0.0004, PRK: 0.0000, KTN: 0.0035, PHG: 0.0000, TRG: 0.0272, SBH: 0.0027, and SWK: 0.0017). In contrast, there was no statistically significant difference in the annual unemployment rates between PNG (*p*-value = 0.5689), KUL (*p*-value = 0.5754), PJY (*p*-value = 0.4473), SGR (*p*-value = 0.8402), JHR (*p*-value = 0.3312), MLK (*p*-value = 0.1636), NSN (*p*-value = 0.2440), and LBN (*p*-value = 0.7279).

From a Malaysian labor market perspective, female unemployment rates were higher than male rates, despite females having higher educational attainment. This disparity was impacted by factors such as traditional biases, limited working options, lack of societal support, and youth dependencies (Abiddin & Ismail 2021; Wei & Cinn 2021). Particularly, the youth labor force aged 15-24 encountered education quality deficiencies and skills mismatch, leading to more severe job losses after economic recessions in 1997-1998 and 2008-2009 (Aun 2020). This situation contributes to endemic income inequality and poverty, making female labor force participation a crucial determinant of the economy (Tafran *et al.* 2020; Abiddin & Ismail 2021).

The statistical evidence for identifying principal characteristics for developing ARIMA models is depicted in Table 3. The superior ARIMA models, selected through the Hyndman-Khandakar algorithm, are presented in Table 4. KPSS tests (Table 3) revealed non-stationarity in the annual unemployment rates time series datasets for KUL, SGR, and SWK, requiring first-order differencing to fulfill the assumptions of ARIMA models as in Table 4. Moreover, the Keenan test conveyed statistically significant nonlinearity in the annual unemployment rates for PHG, TRG, and SBH, leading to SVR-based and single-stacked SVR-Bayesian-based models that were more effective than the ARIMA model for these datasets. The ARIMA models are bottom-ranked on average compared to other SVR-based and single-stacked SVR-Bayesian-based models.

Table 4: Performance of models for the female labor market

Region	State	Model	GoF statistics			Rank
			MAPE	MAE	RMSE	
Northern	KDH	ARIMA(1,0,0)	14.5410	0.4747	0.5994	7
		ε-SVR	10.5837	0.3649	0.4861	3
		υ-SVR	10.7370	0.3646	0.4651	4
		FFNN	12.1904	0.4123	0.5240	5
		M_9^P	**5.9120**	**0.1921**	**0.2012**	**1**
		M_{10}^P	7.0935	0.2303	0.2382	2
		M_{11}^P	14.3211	0.4594	0.6156	6
	PRK	ARIMA(0,0,0)	12.5130	0.4893	0.6177	**7**
		ε-SVR	10.3990	0.4108	0.5388	3
		υ-SVR	11.2063	0.4486	0.5372	4
		FFNN	11.4810	0.4487	0.5812	5
		M_9^P	**3.8676**	**0.1520**	**0.1583**	**1**
		M_{10}^P	4.6686	0.1834	0.1902	2
		M_{11}^P	11.9640	0.4659	0.5888	6
	PLS	ARIMA(0,0,0)	21.6356	0.7657	0.9743	7
		ε-SVR	16.2670	0.6044	0.8443	4
		υ-SVR	16.3920	0.6079	0.8218	5
		FFNN	17.1013	0.6576	0.8575	6
		M_2^P	9.4866	0.3444	0.3665	3
		M_3^P	**3.1528**	**0.1109**	**0.1309**	**1**
		M_4^P	7.1190	0.2429	0.2855	2
	PNG	ARIMA(0,0,0)	25.4421	0.3612	0.4602	7
		ε-SVR	19.5635	0.2983	0.4041	4
		υ-SVR	21.5141	0.3211	0.4085	5
		FFNN	23.1241	0.3300	0.4377	6
		M_1^P	5.8717	0.0918	0.1014	3
		M_7^P	3.7190	0.0577	0.0667	2
		M_8^P	**1.9791**	**0.0297**	**0.0374**	**1**
East Coast	KTN	ARIMA(1,0,0)	17.7698	0.5937	0.7167	6
		ε-SVR	13.5596	0.4225	0.5463	4
		υ-SVR	14.0035	0.4576	0.5530	5
		FFNN	17.8695	0.5911	0.7235	7
		M_8^P	**6.1018**	**0.2032**	**0.2118**	**1**
		M_9^P	7.7092	0.2576	0.2653	2
		M_{10}^P	8.8802	0.2962	0.3062	3

Table 4 (Continued)

	PHG	ARIMA(0,0,0)	11.9800	0.4553	0.5903	7
		ε-SVR	10.7927	0.3957	0.5427	5
		υ-SVR	11.4526	0.4297	0.5387	6
		FFNN	10.2807	0.3760	0.4882	4
		M_6^P	**3.9078**	**0.1493**	**0.1648**	**1**
		M_7^P	5.3015	0.2042	0.2201	2
		M_8^P	6.6265	0.2548	0.2726	3
	TRG	ARIMA(0,0,0)	14.8253	0.6038	0.8815	7
		ε-SVR	13.6316	0.5707	0.8685	6
		υ-SVR	13.5551	0.5734	0.8636	5
		FFNN	11.2701	0.4176	0.5151	4
		M_1^P	4.4003	0.1686	0.1764	3
		M_5^P	2.5100	0.0956	0.1101	2
		M_6^P	**0.9374**	**0.0353**	**0.0448**	**1**
Central	KUL	ARIMA(0,1,0)	16.0538	0.4732	0.6186	6
		ε-SVR	12.4827	0.3508	0.4558	3
		υ-SVR	13.5186	0.3823	0.4760	4
		FFNN	14.6149	0.4137	0.5081	5
		M_9^P	**6.9266**	**0.1845**	**0.1905**	**1**
		M_{10}^P	7.9444	0.2119	0.2167	2
		M_{11}^P	17.6957	0.4593	0.5888	7
	PJY*	ARIMA(0,0,0)	26.4317	0.3120	0.3583	7
		ε-SVR	20.1517	0.2123	0.2983	3
		υ-SVR	22.3681	0.2569	0.2950	4
		FFNN	20.0002	0.2282	0.2858	2
		M_2^P	23.9492	0.3076	0.3408	6
		M_3^P	**13.4590**	**0.1485**	**0.1713**	**1**
		M_{11}^P	23.0638	0.3236	0.4111	5
	SGR	ARIMA(0,1,0)	20.6789	0.4770	0.6469	7
		ε-SVR	17.7305	0.3786	0.5150	4
		υ-SVR	17.0260	0.3733	0.4977	3
		FFNN	20.5791	0.4349	0.5541	6
		M_9^P	**3.1437**	**0.0650**	**0.0726**	**1**
		M_{10}^P	3.7405	0.0754	0.0836	2
		M_{11}^P	20.5204	0.3389	0.4661	5
Southern	JHR	ARIMA(1,0,0)	20.8594	0.5599	0.6581	6
		ε-SVR	17.4551	0.4699	0.5557	3
		υ-SVR	19.4005	0.5231	0.5876	4
		FFNN	19.5765	0.5250	0.6265	5
		M_9^P	**4.4562**	**0.1182**	**0.1249**	**1**
		M_{10}^P	5.3554	0.1436	0.1498	2
		M_{11}^P	21.8981	0.5706	0.6495	7
	MLK	ARIMA(0,0,1)	37.3861	0.6071	0.7304	7
		ε-SVR	23.9711	0.4684	0.7350	4
		υ-SVR	32.2054	0.5344	0.7109	6
		FFNN	24.5362	0.3659	0.4603	5
		M_2^P	7.2490	0.1114	0.1229	3
		M_3^P	**2.9781**	**0.0459**	**0.0580**	**1**
		M_4^P	4.2970	0.0635	0.0741	2
	NSN	ARIMA(1,0,0)	14.1893	0.4329	0.5661	7
		ε-SVR	7.1093	0.2439	0.3769	4
		υ-SVR	7.4023	0.2527	0.3751	5
		FFNN	12.1457	0.3899	0.4815	6
		M_1^P	4.9536	0.1550	0.1606	3
		M_2^P	**2.8025**	**0.0866**	**0.0940**	**1**
		M_5^P	3.7892	0.1186	0.1269	2

Table 4 (Continued)

Sabah	LBN	ARIMA(0,0,1)	34.5712	1.2742	1.6959	2
		ε-SVR	34.5900	1.3140	1.8359	3
		υ-SVR	38.1767	1.5274	1.7556	4
		FFNN	**31.0442**	**1.1096**	**1.5437**	**1**
		M_8^P	82.2668	3.6590	3.8252	5
		M_9^P	96.6010	4.2950	4.4641	6
		M_{10}^P	110.5954	4.9146	5.0977	7
	SBH	ARIMA(0,0,0)	12.3530	0.7473	0.9287	7
		ε-SVR	9.5795	0.6003	0.8388	3
		υ-SVR	10.3021	0.6253	0.8059	4
		FFNN	11.5221	0.6883	0.8832	6
		$\mathbf{M_9^P}$	**2.0630**	**0.1205**	**0.1318**	**1**
		M_{10}^P	2.3731	0.1411	0.1516	2
		M_{11}^P	11.3804	0.6872	0.8558	5
Sarawak	SWK	ARIMA(0,1,0)	10.8573	0.4926	0.6367	6
		ε-SVR	8.2092	0.3808	0.5154	3
		υ-SVR	8.8339	0.4089	0.5160	5
		FFNN	8.6333	0.3765	0.4963	4
		$\mathbf{M_9^P}$	**3.4552**	**0.1506**	**0.1547**	**1**
		M_{10}^P	3.9612	0.1727	0.1795	2
		M_{11}^P	14.9052	0.6723	0.8300	7

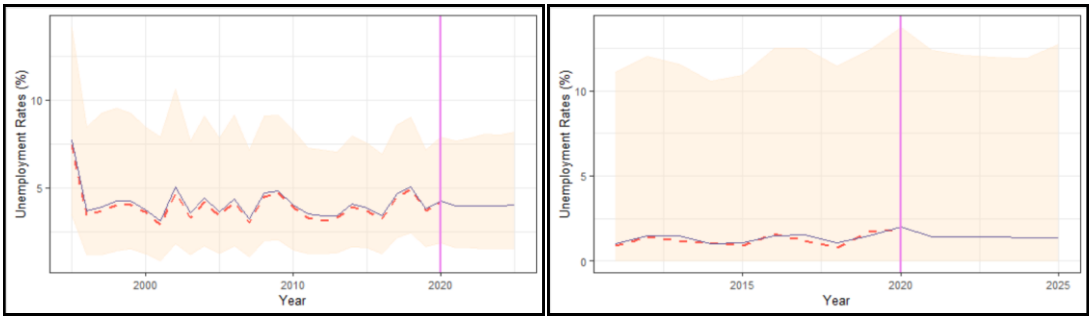
***Note:** SSVREBB models: $\Pr(\theta_t|y_t, n_t, \alpha, \beta)$, $\mathbf{M_1^P}$: $\alpha = \beta = 0.1$, $\mathbf{M_2^P}$: $\alpha = \beta = 0.2$, $\mathbf{M_3^P}$: $\alpha = \beta = 0.3$, $\mathbf{M_4^P}$: $\alpha = \beta = 0.4$, $\mathbf{M_5^P}$: $\alpha = \beta = 0.5$, $\mathbf{M_6^P}$: $\alpha = \beta = 0.6$, $\mathbf{M_7^P}$: $\alpha = \beta = 0.7$, $\mathbf{M_8^P}$: $\alpha = \beta = 0.8$, $\mathbf{M_9^P}$: $\alpha = \beta = 0.9$, $\mathbf{M_{10}^P}$: $\alpha = \beta = 0.3$; SSVRHBB model: $\mathbf{M_{11}^P}$: $\Pr(\theta_t, \mu, \tau|y_t, n_t)$.

Additionally, the presence of a statistically significant monotonic trend in JHR's annual unemployment rate was detrended utilising a first-order autoregressive. Meanwhile, there are no statistically significant seasonal characteristics exhibited in female annual unemployment rates time series datasets for all states and territories, which is consistent with the results from non-seasonal ARIMA models as depicted in Tables 3 and 4. The superior ARIMA models for all states and territories did not require integration with the GARCH model, and no statistically significant ARCH influence resulted in these time series datasets.

In summary, the SSVREBB models outperformed the ARIMA, SVR-based, and SSVRHBB models in projecting female annual unemployment rates. Except for LBN, SSVREBB models ranked highest in 15 of the 16 (93.75%) states and territories, with different fixed values for hyperparameters α and β. This finding aligned with the conclusion for male unemployment rates in Section 3.1. Conversely, the FFNN model ranked highest for LBN. The analysis results revealed that SSVREBB models consistently outperformed others in predicting female unemployment rates across regions and Malaysian states on average, which is consistent with the findings for male unemployment rates discussed earlier.

In terms of model performance, the findings suggest that the proposed SSVREBB models are more dynamic and robust when fitting the limited time series datasets across genders, regions, and states. These datasets exhibit various nonlinear characteristics, challenging the pre-defined assumptions of traditional statistical models, particularly regarding stationarity, nonlinearity, trend, and seasonality. Additionally, these results reinforce the limitations discussed in the introduction section, noting that traditional statistical and AI-based models struggle with limited datasets containing fewer than 30 observations. Nevertheless, the results demonstrate that different values for α and β are essential to optimise predictive accuracy for time series datasets with varying characteristics.

Figure 7 depicts the examples modeled and forecasted future 5-year unemployment rates utilising the SSVREBB models with α=β=0.9 (M_6^P) and M_3^P of TRG and PJY. These models were selected based on their minimum and maximum arithmetic averages for GoF statistics (MAPE, MAE, and RMSE). In particular, TRG and PJY, respectively, exhibited the best and poorest prediction performance among the 15 superior SSVREBB models across the regions, states, and territories. The red dashed and navy-blue lines represented the observed and predicted annual unemployment rates, while the shaded region conveyed the 95% HDR of the predicted rates as discussed in Section 3.1. The predicted future 5-year unemployment rates were considered reasonable with the effective implementation of initiatives by policymakers, as outlined in the 13MP and the MADANI Economy Framework.



(a) (b)

Figure 7: Examples of forecasted 5-year unemployment rates (navy-blue lines after 2020) for (a) TRG and (b) PJY, respectively

The forecasted results for 2021 and 2022 can be validated by actual observations. For TRG, the actual unemployment rates for 2020, 2021, and 2022 were 4.2%, 5.0%, and 4.8%, respectively (Department of Statistics Malaysia n.d.). The 2021 forecasted rate was inaccurate, likely due to the impact of the Movement Control Order (Bernama 2021), which was not factored into the proposed single-stacked SVR-Bayesian-based models. However, state-level initiatives such as the *Penjana* Career Carnival have aided in reducing the unemployment rate, as evidenced in subsequent years (Bernama 2021). In contrast, LBN's actual unemployment rates in 2020, 2021, and 2022 were 1.9%, 2.0%, and 1.7%, respectively, supporting the forecasted trends in the state, with the exception of the 2021 rate, which slightly deviated due to the COVID-19 pandemic.

Overall, these findings provide critical insights for policymakers, particularly in addressing the gender gap in labor force participation, a key sub-index in the Malaysia Gender Gap Indices (MGGI). The results are aligned with the 13MP and the MADANI Economy Framework's objective of increasing female labor market participation to 60% (Ministry of Finance 2023), and reducing income inequality across gender, ethnicity, and region. For instance, the recently launched Talent Corporation's Wanita MyWIRA initiative (TalentCorp Group of Companies 2024) has shown promise in improving female labor force participation in regions such as KDH, PLS, PRK, KTN, PHG, TRG, SBH, and SWK, where statistics indicate significant disparities. These insights are not merely relevant to Malaysia but also offer guidance to global policymakers addressing gender-based labor market disparities. This aligns with key SDGs such as SDG1 (No Poverty), SDG4 (Quality Education), SDG5 (Gender Equality), and SDG8 (Decent Work and Economic Growth). This research contributes to the broader discussion on promoting gender inequality, economic inclusion, and advancing female labor force participation in the context of IR4.0, while also recognising potential challenges in implementing these recommendations and providing strategies and instances to overcome them, including community awareness programs and advocacy initiatives to promote gender equity.

5. Conclusion and Future Work

In this article, two Bayesian-based models, SSVREBB and SSVRHBB, were utilised to model and forecast the annual unemployment rates by gender across regions, and Malaysia's states and federal territories. The effectiveness of these models was compared with 11 other single-stacked SVR-Bayesian-based and well-known models, ranked utilising the VIKOR-based Taguchi optimisation algorithm. The SSVREBB model outperformed the other proposed and benchmark models, demonstrating a superior fit for both male and female unemployment rates. The findings indicate that the proposed SSVREBB models are dynamic and robust, particularly when dealing with limited time series datasets that exhibit various nonlinear characteristics. These results reaffirm the limitations of traditional statistical and AI-based models, which struggle with datasets containing fewer than 30 observations, particularly in terms of addressing stationarity, nonlinearity, trend, and seasonality.

These models serve as the benchmark for labor force market analysis in Malaysia, yielding insights for policymakers to address severe unemployment rates in regions such as LBN and SBH, especially among the female youth labor force. Improving education quality and addressing skills mismatches were identified as critical strategies. Additionally, promoting female labor force participation emerged as a means to reduce gender-based income inequality and poverty, aligning with the objectives of Malaysia's 13MP and the MADANI Economy Framework, which aims to raise women's labor market participation to 60%.

These insights are not merely relevant to Malaysia but also offer guidance to global policymakers addressing gender-based labor market disparities. The approach aligns with key SDGs, including SDG1 (No Poverty), SDG4 (Quality Education), SDG5 (Gender Equality), and SDG8 (Decent Work and Economic Growth). Future research should focus on developing superior models to analyse underemployment rates and real wages, incorporating national GDP and economic activities. This study recommends designing automated algorithms to optimise α and β, and initial forecasting values for unemployment rates, thereby enhancing the effectiveness of the SSVREBB models. Furthermore, the application of these models to labor market datasets from other nations could validate their effectiveness and allow for the generalisation of insights across different contexts. By adapting the proposed models to specific nations or regional circumstances, policymakers worldwide can develop inclusive and effective economic policies.

This article also proposes to extend the study by incorporating key determinants aligned with the Sustainable Development Goals (SDGs), including environmental, economic, human, and social factors. This approach aims to develop multivariable and multivariate models that not merely validate the effectiveness of the proposed single-stacked AI-Bayesian-based models but also assess the sensitivity of the models' outcomes to variations in these key determinants. Such understanding will enhance the insights into how different factors influence the predictive performance and robustness of these models.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT to improve the readability and language of this work. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Statistics & Data Analytics Research Cluster
Center for Mathematical Sciences
Universiti Malaysia Pahang Al-Sultan Abdullah
Lebuh Persiaran Tun Khalil Yaakob
26300 Kuantan
Pahang, MALAYSIA
*E-mail: chuanzl@umpsa.edu.my**

Faculty of Industrial Management
Universiti Malaysia Pahang Al-Sultan Abdullah
Lebuh Persiaran Tun Khalil Yaakob
26300 Kuantan
Pahang, MALAYSIA
E-mail: chia@umpsa.edu.my

Department of Mathematics and Statistics
Faculty of Science
Universiti Putra Malaysia
43400 UPM Serdang
Selangor, MALAYSIA
E-mail: sy_ling@upm.edu.my

Department of Mathematical Sciences
Faculty of Science and Technology
Universiti Kebangsaan Malaysia
43600 UKM Bangi
Selangor, MALAYSIA
E-mail: ni@ukm.edu.my

Technopreneurship Department
Faculty of Technology Management and Technopreneurship
Technology Campus
Universiti Teknikal Malaysia Melaka
Hang Tuah Jaya
76100 Melaka, MALAYSIA
E-mail: famsoofen@utem.edu.my

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*Corresponding author