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Research article

A Web-Based Forecasting Approach to Estimating the Number of Low-Income Households Eligible for Social Food Aid Using Holt's Double Exponential Smoothing

Mukhamad Masrur [a,], Solikhin Solikhin [b], Muhammad Walid Syahrul Churum [c], M. Zakki Abdillah [d], Toni Wijanarko Adi Putra [e]*

[a,c] *Department of Information Systems, Universitas Pesantren Tinggi Darul Ulum, Jl. KH. As'ad Umar No. 1 Peterongan, Jombang 61481, Indonesia*
[b] *Department of Informatics Engineering, STMIK Himsya, JL. Raya Karanganyar Tugu KM. 12 No. 58, Semarang 50152, Indonesia*
[d] *Department of Information Systems, Universitas Nasional Karangturi, Jl. Raden Patah No.182-192 Rejomulyo, Kota Semarang 50227, Indonesia*
[e] *Department of Informatics Engineering, Universitas Sains dan Teknologi Komputer, Jl. Majapahit No. 605 Pedurungan Kidul, Kota Semarang 50192, Indonesia*
email: [a,*]mukhamadmasrur@ft.unipdu.ac.id, [b]solikhin@stmik-himsya.ac.id, [c]walidsyahrulw@gmail.com, [d]m.zakki.abdillah@gmail.com, [e]toni.wijanarko@stekom.ac.id
* Correspondence

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ABSTRACT

This work presents a web-based forecasting methodology for predicting the quantity of low-income households qualified for social food assistance utilizing Holt's Double Exponential Smoothing (HDES) technique. Precise assessment is crucial for governmental bodies and social welfare organizations to guarantee efficient aid distribution and effective resource allocation. The proposed method amalgamates time series forecasting models with a web-based application to deliver real-time predictions and accessibility for decision-makers. Historical data on low-income household statistics were employed to formulate and authenticate the forecasting model. The findings indicate that HDES delivers dependable short-term predictions with low error rates, accurately reflecting patterns in the data. This online application offers policymakers an effective means for monitoring socio-economic trends and enhancing the responsiveness of social assistance initiatives. This research contributes by integrating statistical forecasting with web-based applications to aid social policy decisions.

1. Introduction

All countries, policymakers, and stakeholders are encouraged to implement strategic plans aimed at liberating individuals from the grip of poverty and advancing overall well-being [1]. Wigle et al. [2] found that poverty alleviation accounted for 61% of the observed decline in stunting rates. Economic well-being refers to the income earned or provided under specific conditions to enhance the quality of life of families [3]. Income level plays a significant role in reducing stunting rates [4, 5].

Despite ongoing efforts, access to nutritious and adequate food remains a major challenge for low-income households across the globe [6]. These households continue to experience food insecurity, making them key beneficiaries of targeted social food assistance programs [7]. Oderinde et al. [8]

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determined that governmental action, including the augmentation of food production, is essential for food security. Government action is crucial for augmenting income, especially for low-income individuals, which will influence consumption levels [9]. However, Hamzah et al. [10] determined that the influence of per capita income, poverty severity index, and government expenditure on education and health on stunting levels remain unclear.

However, the Indonesian government has implemented a range of family welfare programs over the years, including initiatives to promote the consumption of nutritious food, a 12-year compulsory education program for children, programs aimed at reducing maternal and infant mortality rates, economic empowerment initiatives for families, and women's empowerment programs. Roediger et al. [4] point out the importance of maternal education in mitigating stunting. These efforts form part of the broader strategy to achieve the Sustainable Development Goals (SDGs) [11].

Social protection and security programs in Indonesia are primarily targeted at low-income populations, as identified in the Integrated Social Welfare Data (DTKS). One of the flagship programs designed to reduce poverty is the Family Hope Program (PKH). PKH is a conditional cash transfer program that provides social assistance to underprivileged families, contingent upon their compliance with specific program requirements. The need for such social protection programs continues to grow, especially in addressing persistent poverty-related challenges [11].

According to the Central Statistics Agency (BPS), the profile of the number of beneficiary families and the Social-Food Assistance Budget in East Java has either increased or decreased. The local government continues to seek solutions to this problem to estimate the increase or decrease in the number of beneficiary families and the social-food assistance budget in East Java Province.

Related parties need to pay closer attention to shifts and uncertainties in the budget and number of families receiving social food aid in East Java Province because they must make accurate policy decisions within a specific time frame. Predicting the number of households that will benefit from social food aid and the corresponding budget with accuracy is essential because it enables local governments to address community needs while preserving community confidence. Additionally, estimating the budget and number of families eligible for social food assistance will assist regional governments in deciding on the best course of action to revive the local economy. This will impact community income and expenses, business growth, and the more effective use of both human and natural resources. Forecasting is the ability to anticipate future events based on current information. It requires the use of historical data and knowledge while making forecasts. Historical data and information consist of observations that took place during that period under different circumstances [12]. To achieve accurate estimation, it is crucial to first select the appropriate modeling approach [13].

To examine the trend movements in previous data patterns, predictions are required for the number of beneficiary families and the social food assistance expenditures in East Java Province over the next few years. In this way, related parties can develop strategic policies to address these issues. HDES is one forecasting technique. Using historical data, this technique forecasts the future. HDES works well for short-, medium-, and long-term forecasting applications.

Using this data, we aim to forecast the following issues, which represent the most fundamental problem formulations: (a) How can the HDES method be used to forecast changes and uncertainties in the number of beneficiary families and the social food assistance budget, specifically in relation to the number of people living in poverty (JPM), the percentage of the impoverished (PPM), the poverty line (GK), the gap (P1), and the severity index (P2)? (b) How can a web-based prediction system be constructed that incorporates the HDES method?

A prior study suggested using the exponential smoothing (ES) model for temperature data in the literature [14]. Research in [15] modeled univariate temperature data for climate using DES and Single Exponential Smoothing (SES) models. For univariate time series (TS) data, ES is one of the most widely used forecasting techniques [16]. The ES approach uses the most recent data to perform a continuous calculation that yields the average (smoothing) of historical data [17]. Xu et al. [18] predicted heart problems in newborns: a comparison of Holt-Winters exponential smoothing and ARIMA models. Forecasting with DES models can be summed up as follows: determining the best smoothing constants, applying the forecasting equation, and calculating the initial values [19].

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This method's fundamental principle is that the exponential window function can be used to smooth the TS since it is stable. ES is classified into three categories according to its frequently of application: SES, DES, and triple exponential smoothing (TES) [20]. Rushton et al. [21] estimated pharmaceutical stock inventories using Holt Winters seasoning, ES, and linear regression. Furthermore, for medications in a newly established medical center hospital, moving average (MA), ES, and Holt Winter seasoning were estimated [22]. Satrio et al. [23] forecast household appliances using SES, MA, and linear regression.

Making future projections is crucial for problem-solving in planning and strategy. Selecting an appropriate modeling strategy at the outset is crucial for performing precise estimations [13]. By carefully and realistically analyzing newly surfaced information from the past to the present in the form of a TS, we can achieve successful management decision-making. For example, the ES approach has been used to estimate the number of firefighter interventions [24]. Meanwhile, the study in [25] conducted a comparison of the Holt, Brown, and Damped methods (DES variants) on global commodity price data as an empirical example of the application and evaluation of the exponential smoothing model.

In this study, we applied the HDES approach to forecast the budget and number of families receiving social food aid in East Java Province. The East Java Province BPS provided data on the evolution of the GK, P1, P2, JPM, and PPM for the years 2012–2023.

Using trend patterns [26], we can apply exponential smoothing (ES), a TS modeling method, to forecasting [27]. Numerous relevant studies have investigated the use of predictions in conjunction with ES to address a variety of issues. Researchers [28] proposed a TS model incorporating ES techniques to predict the calving dates date of dairy cow calving. An ES approach with hyperparameter tweaking was used to predict the number of pandemic cases [29]. According to research using ES [30], experiments projected the impact and spread of COVID-19, primarily affecting Black populations in the United States. Meanwhile, the study in [31] experiment forecasts the current status of the COVID-19 epidemic using Holt's linear trend exponential smoothing technique.

Research [32] proposed SES and DES methods for filtering distorted radar data. The study [33] used the ARIMAX and DES prediction methods to estimate polycrystalline photovoltaic generation. Study [34] extends exponential smoothing to multivariate cases with a model taxonomy, relevant to DES/Holt variants for vector and seasonal data. The paper [35] introduces a medical picture registration strategy that updates weights and transformation parameters using DES. The Knative Autoscaler optimization in paper [36] leverages DES to optimize the pod count. Study [37] presents robust parameter estimation for exponential smoothing (SES/DES/TES) to optimize α/β and enhance DES robustness to outliers. A different study [38] used rainfall data from the Indian Meteorological Department to examine the effectiveness of TS forecasting models, including ES, SES, DES, TES, ARIMA, and SARIMA models, in predicting floods. Rabbani et al. [39] compared ES-based time series models with SARIMA models for forecasting traffic incidents in Pakistan. The findings indicate that, compared to the SARIMA model, the ES model provides a closer fit to the accident data. Meanwhile, the study referenced in [40] applies the exponential smoothing family (ES/TES) models to the forecasting of cellular network traffic data. This experimental procedure selects the model with the lowest RMSE value among the three types of techniques. The findings demonstrate that the ES approach performs better than the multiplicative seasonal ARIMA model.

The results indicate that the HDES statistical forecasting method is superior to the artificial neural network (ANN) model. The experiment in [41] calculated the company's six-year coal production demand. Zaini et al. [42] provide an estimation of Malaysian stock price fluctuations utilizing the HDES approach and the ANN model. Some domain-specific studies have reported that traditional ES methods can outperform neural network models in certain forecasting tasks, particularly for shorter or less volatile time series [43]. Furthermore, to forecast the number of passengers on trains, [44, 45] used the HDES approach in conjunction with a fuzzy time series rate of change model. The study in [46] examined TS forecasting to predict the number of international visitors to North Sumatra. Upon comparing the three methods, HDES and Brown DES emerged as the most successful, achieving the lowest MAPE scores of 12.21% and 12.71%, respectively, while the Double MA method produced a result of 14.12%.

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Research [47] compares two forecasting techniques, the DES and TES approaches. Based on the conducted trials, the forecasting findings indicate that the DES approach yields more optimal results. In the experiment reported in [48], researchers built and executed an inventory forecasting system using the DES approach. Subsequent observations [49] also utilized the DES approach to develop an inventory forecasting system in their study. This study [50] uses ES to estimate demand, optimize inventory replenishment, and implement dynamic pricing strategies using established algorithms. The use of several ES techniques for forecasting metal spot prices is presented in this research [51]. The HDES approach was used in the proposal [26] to develop a price prediction system for export products made from swallow's nest. The MAPE test found it at 0.20%, and it received a very good rating in the accuracy category. A DES scheme and parametric models are used in the study [52] to create a monitoring system for photovoltaic systems that is easy to use and works well.

Most prior research employed ARIMA, SES, or ANN for technical forecasting but did not incorporate these methods into a web-based forecasting system for social assistance recipients. While previous research has predominantly emphasized the accuracy and performance of forecasting models, limited attention has been given to their integration into web-based applications. This study bridges that gap by combining statistical forecasting methods, specifically the HDES method, with a digital platform to enhance data-driven decision-making in the context of public welfare management. The proposed web-based system provides a practical and accessible tool for policymakers to monitor socio-economic trends and strengthen the effectiveness and responsiveness of social assistance programs. This contribution is both methodological, as it applies the HDES technique in this context, and practical, as it develops an accessible web system. The objective of this work is to create and validate a web-based forecasting system that employs HDES to estimate the number of low-income households eligible for social food assistance in East Java.

2. Materials and Methods

2.1. Materials

Families classified as impoverished are entitled to social assistance. The BPS measures poverty by evaluating the ability to meet fundamental requirements, using a method referred to as the approach to fundamental needs. According to this definition, poverty is the inability to afford basic needs, including food and non-food items. Therefore, the population classified as poor is defined as those whose average monthly per capita income falls below the national poverty threshold.

The GK is the result of a combination of the food poverty line (GKM) and the non-food poverty line (GKNM). If a person's average monthly per capita income is less than the federal poverty level, they are deemed destitute. The GKM, or minimum daily calorie requirement for food expenditure, is 2100 kilocalories per person. The basic food needs commodity bundle consists of 52 different commodity types, including grains, tubers, fish, meat, eggs, milk, vegetables, nuts, fruit, oils, and fats, among others. The minimal requirements for housing, clothes, health care, and education are known as the GKNM. The basic non-food commodity bundle consists of 47 types of commodities in rural areas and 51 types of commodities in urban areas.

A measure of the portion of the population that falls below the GK is the Head Count Index (HCI-P0). P1 measures the average gap between each impoverished person's expenses and the GK. The index increases with the distance between the average population expenditure and the GK. The P2 provides an overview of how the poor distribute their expenses. With an increasing index value, the gap in impoverished people's expenditures grows.

This study employs a quantitative method to gather data that can be analyzed using statistical, mathematical, and computational approaches in order to conduct a systematic assessment of the distribution of social assistance within communities. The BPS provided official digital secondary data that served as the basis for data collection and experiment material. This study focuses on the growth data prediction of the P1, P2, GK, JPM, and PPM in East Java in 2012–2023, which constitute the main subjects of this study. Table 1 displays the actual data sets.

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Table 1. Real data sets

Year	P1	P2	GK	JPM	PPM
2012	1.93	0.44	243783.00	4992.70	13.08
2013	2.07	0.50	273758.00	4893.00	12.73
...	...	...	...	...	...
2022	1.62	0.38	460909.00	4181.29	10.38
2023	1.63	0.37	507286.00	4188.81	10.35

2.2. Methods

2.2.1. HDES

Within the scope of this investigation, we utilized the HDES method to forecast the growth of low-income families in East Java Province who are eligible to receive social food aid. We conducted this analysis using the P1, the P2, the GK, the JPM, and the PPM datasets. Figure 1 depicts the various phases that make up the prediction process using the HDES method.

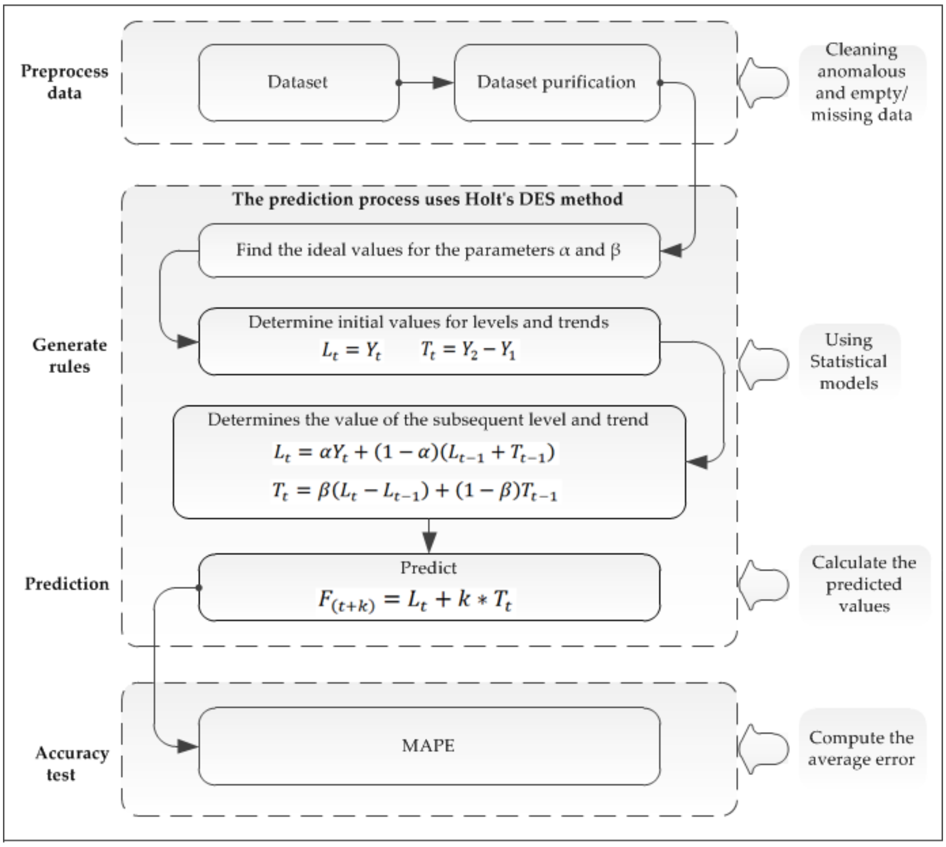

Fig. 1. Phases of the prediction process for the HDES technique

We applied the HDES approach to address discrepancies between observed data and predicted values in the presence of a trend in the plot. We combine and modify the single and double smoothing parameters to account for trends [53]. HDES employs two smoothing parameters, as expressed in equations 1–3.

The Optimal Parameter Selection for HDES Is essential for achieving accurate forecasting . It is crucial to identify the optimal smoothing parameters: α (alpha) as a level smoothing factor and β (beta) as a trend smoothing factor. The optimal values of α and β are usually chosen by minimizing error metrics; here we use the Mean Absolute Percentage Error (MAPE). The process involves iterating over a range of possible values for α and β (e.g., from 0.1 to 1.0) and computing the error for each parameter pair. The pair that yields the lowest error is selected as the optimal parameter set.

Step-by-Step Procedure: (1) Define the data—Historical time series data of low-income household counts; (2) Initialize parameters—Define the search space for α and β (e.g., 0.1 to 1.0); (3) Apply HDES for each (α, β) pair; (4) Calculate forecasted values based on the smoothing equations; (5) Compute error metric (MSE and MAPE); (6) Store and compare errors to determine the best parameter combination; and (7) Return the optimal α and β.

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$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (1)$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (2)$$
$$F_{(t+k)} = L_t + k * T_t \quad (3)$$

L_t represents the level value, and T_t serves as the trend value. This model uses the smoothing parameters α and β. The variable "k" represents the change in the future period to be forecasted, while "t" represents the specific period. "Y_t" denotes the current value of the data, and "F_t" represents the forecasted value. Equations 4 and 5 display the starting values for the level and trend.

$$L_t = Y_t \quad (4)$$
$$T_t = Y_2 - Y_1 \quad (5)$$

Check the model's performance

We measure the effectiveness of the method using MAPE. We used MAPE as a determinant of the optimal alpha and beta parameter values. Furthermore, we computed the mean absolute difference between the values that were forecasted and those that were calculated, or MAPE, as a percentage of the actual values. We calculate MAPE using equation 6.

$$MAPE = \frac{\sum_{t=1}^{n} |Y_t - F_t| \frac{1}{Y_t}}{n} \times 100\% \quad (6)$$

In this case, the data contain a real value of Y_t , F_t represents the predicted value, n is the number of data periods, and t is the t time period.

Significance of MAPE

The forecasting results' accuracy level, based on MAPE values, falls into a specific significance range that signifies the quality of the forecasting results [53]. Significance levels are required in forecasts using MAPE [53], as indicated in Table 2, to prevent various issues with interpreting accuracy measurements in relation to the magnitude of the forecast value.

Table 2. Significance of MAPE

Four categories	Significance
$< 10\%$	Excellent
$10\% - 20\%$	Good
$20\% - 50\%$	Reasonable
$> 50\%$	Bad

2.2.2. Prediction System Design

System Design

The research produces a prediction system that uses real data. The forecasting system can use various parameters, such as the P1, P2, GK, JPM, and PPM, to generate predictions of families receiving social food assistance. The user enters and transmits this data to the server. The server processes and estimates P1, P2, GK, JPM, and PPM. The process diagram of the prediction system is presented in Figure 2.

HDES computations are directly integrated into the CodeIgniter framework via the Des_lp.php, Des_jpm.php, and Des_ppm.php controllers. The iterative selection of alpha and beta values is conducted via these controllers, and the system features a form for choosing α and beta values, making the calculations more dynamic.

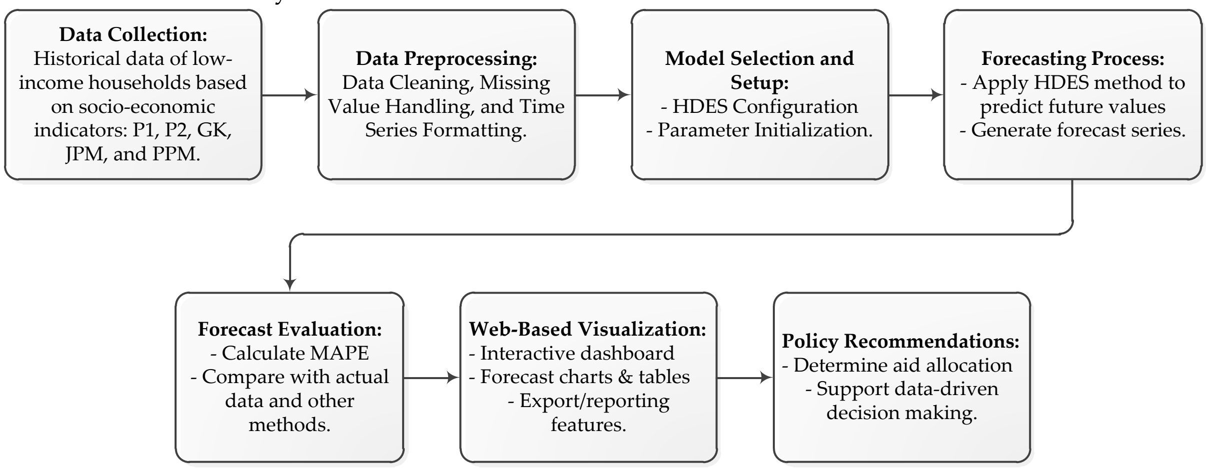

Fig. 2. Prediction system process diagram

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Data Collection: Gather historical data on low-income households based on key socio-economic indicators, including the Poverty Depth Index (P1), Poverty Severity Index (P2), Poverty Line (GK), Number of Poor People (JPM), and Poverty Rate (PPM).

Data Preprocessing: Perform data cleaning, handle missing values, and format the dataset into a structured time series suitable for forecasting analysis.

Model Selection and Configuration: (a) Configure the HDES model, and (b) Initialize model parameters based on data characteristics.

Forecasting Process: (a) Apply the HDES method to estimate future values of socio-economic indicators, and (b) Generate the forecast series for each indicator.

Forecast Evaluation: (a) Evaluate forecasting performance using error metrics: Mean Absolute Percentage Error (MAPE), and (b) Compare results with actual observations and alternative forecasting methods: SES, ARIMA, and ANN model.

Web-Based Visualization: (a) Develop an interactive dashboard for analysis, (b) Display forecast results through charts and tables, and (c) Provide export and reporting functionalities for stakeholders.

Policy Recommendations: (a) Use forecast insights to guide the allocation of social assistance, and (b) Support evidence-based policy decisions for poverty alleviation and welfare planning.

The development of the web-based forecasting system requires a set of specific technical components to ensure functionality, efficiency, and ease of maintenance. The system is hosted on an Apache 2.0 web server, providing a reliable and widely supported environment for web application deployment. The development hardware comprises an Intel Core i7 processor, 16 GB of RAM, and integrated VGA. The software utilized includes the Windows 11 operating system, PHP version 7.4.3, MySQL version 7.4.3, Apache version 2.0, and CodeIgniter version 3.1.13. The operating system and testing environment employed are Microsoft Windows 11 and macOS Sequoia 15.6.1. The devices utilized for testing consist of a MacBook Pro 2019, an iPhone SE 2, and a Xiaomi Poco M6 Pro. Figure 3 represents a basic block diagram that illustrates the workflow.

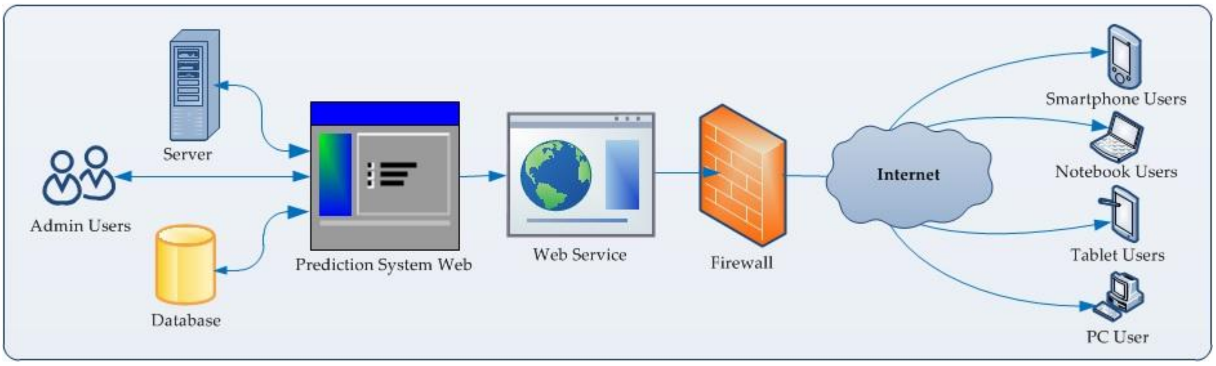

Fig. 3. Prediction system web diagram

Figure 4 depicts the system process, highlighting the interaction between the user, the web application, the database, the forecasting module, and the visualization/dashboard.

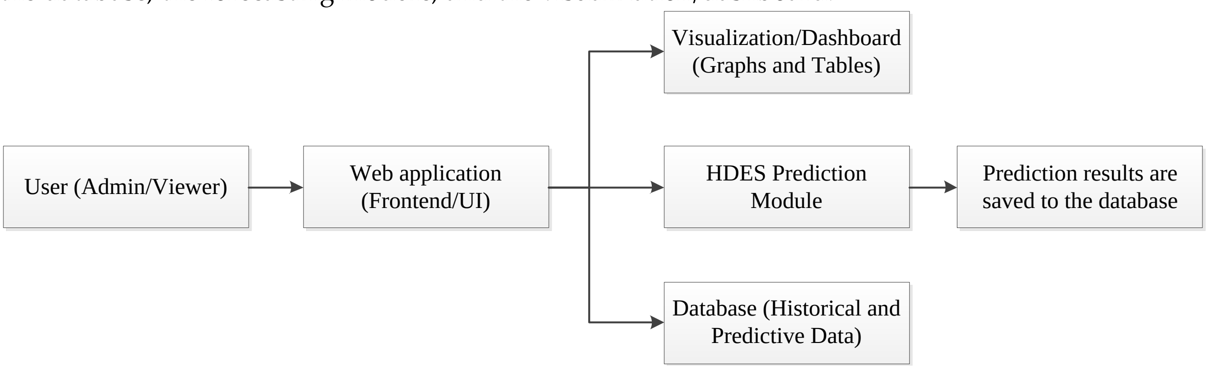

Fig. 4. Diagram of user interaction with a web application

Capturing Information

The database server stores the recorded P1, P2, GK, JPM, and PPM data. This information is used to forecast P1, P2, GK, JPM, and PPM over the next few years or periods using a web-based forecasting system that applies the statistical HDES method.

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Historical Information

Data gathered in the past is known as historical data. The forecasting system makes use of this data to enhance forecasting accuracy. This technique derives estimations from historical data spanning up to twelve years or periods.

System of Forecasting

We gathered and processed the data using the HDES technique. We include the year or period along with the corresponding P1, P2, GK, JPM, and PPM data values. The goal of the HDES statistical technique approach was to achieve a very good MAPE significance with an average forecasting error of less than 10%. Equations 1 to 5 outline the steps in HDES technique.

Mean Predictive Error

The forecasting system verifies the accuracy of the predicted outcomes. The forecasting system evaluates one primary type of error: MAPE. The 6 equation displays the MAPE formulas.

3. Results and Discussion

Figures 5 to 9 show how the HDES model performs in comparison to real values. We determined the optimal values for the α and β parameters to produce these performance outcomes based on the minimum MAPE values, as indicated in Table 3.

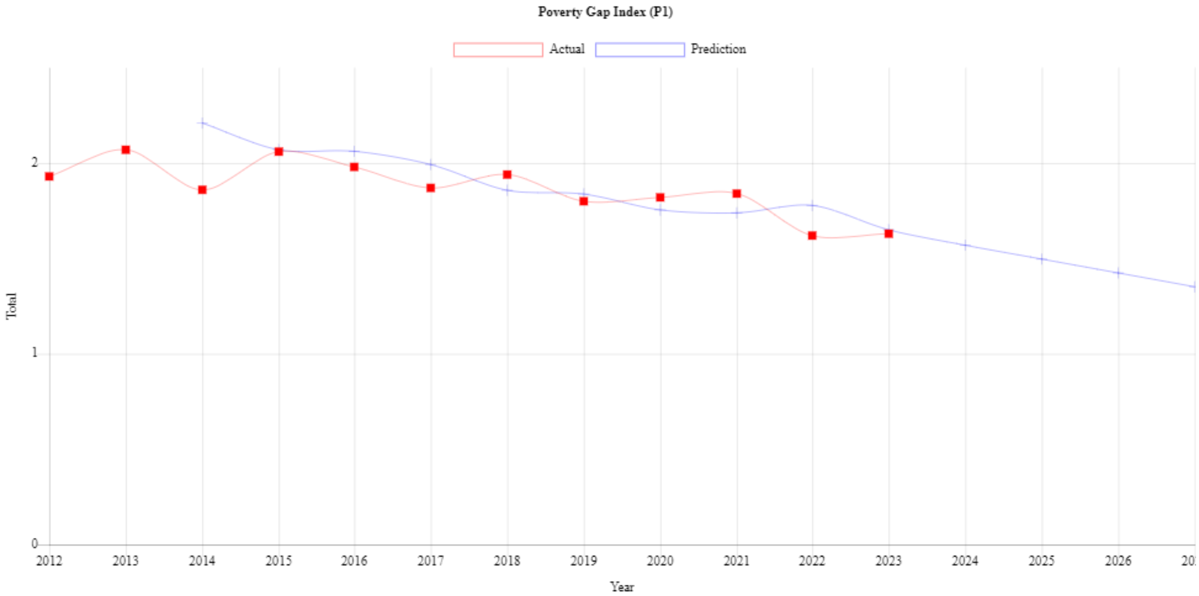

Fig. 5. P1 prediction results using MAPE to determine the optimal α and β parameters

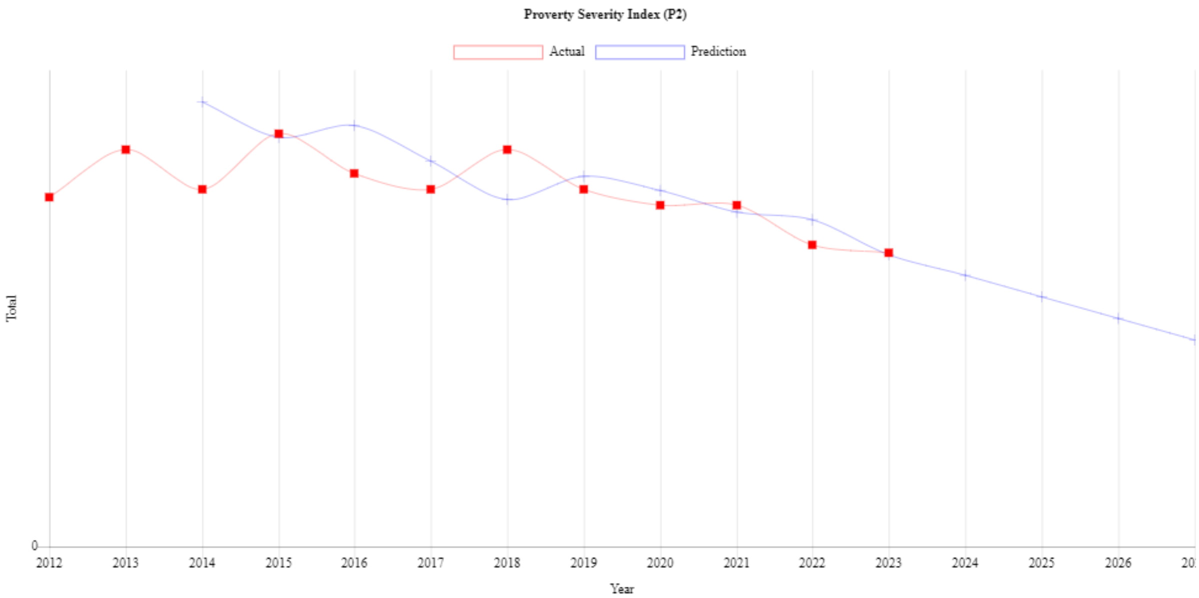

Fig. 6. P2 prediction results using MAPE to determine the optimal α and β parameters

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Table 3. Optimal Parameter Selection

Poverty and Inequality	Α	β	MAPE
P1	0.40	1.00	0.0563951622
P2	0.50	0.90	0.0775199521
GK	1.00	1.00	0.0209505344
JPM	0.20	0.50	0.0321749656
PPM	0.20	0.70	0.0333871875

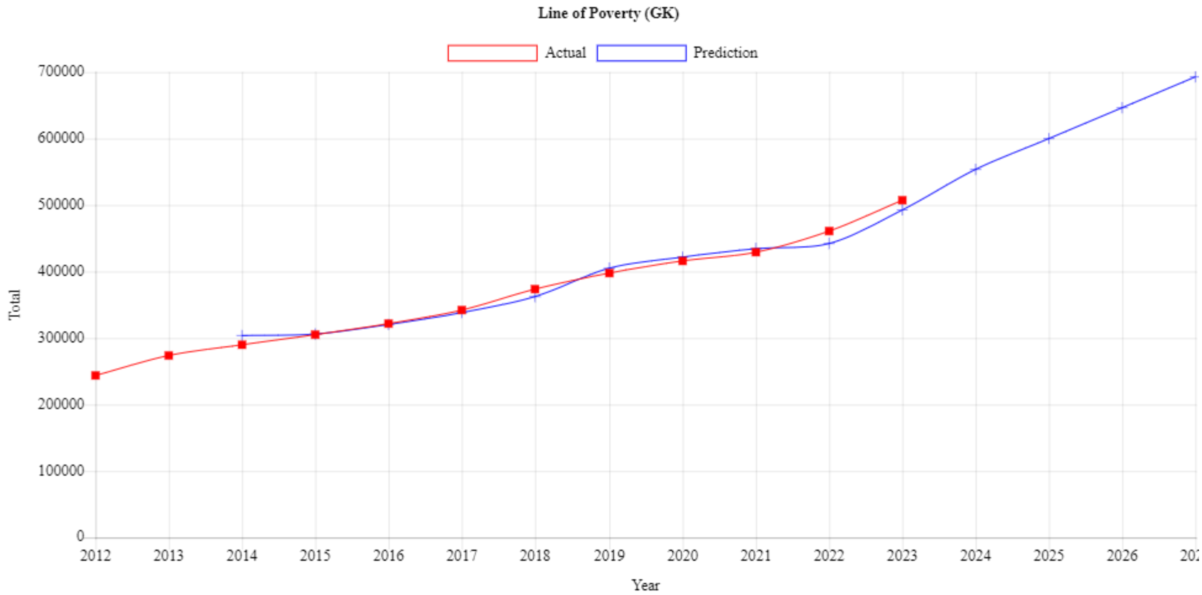

Fig. 7. GK prediction results GK using MAPE to determine the optimal α and β parameters

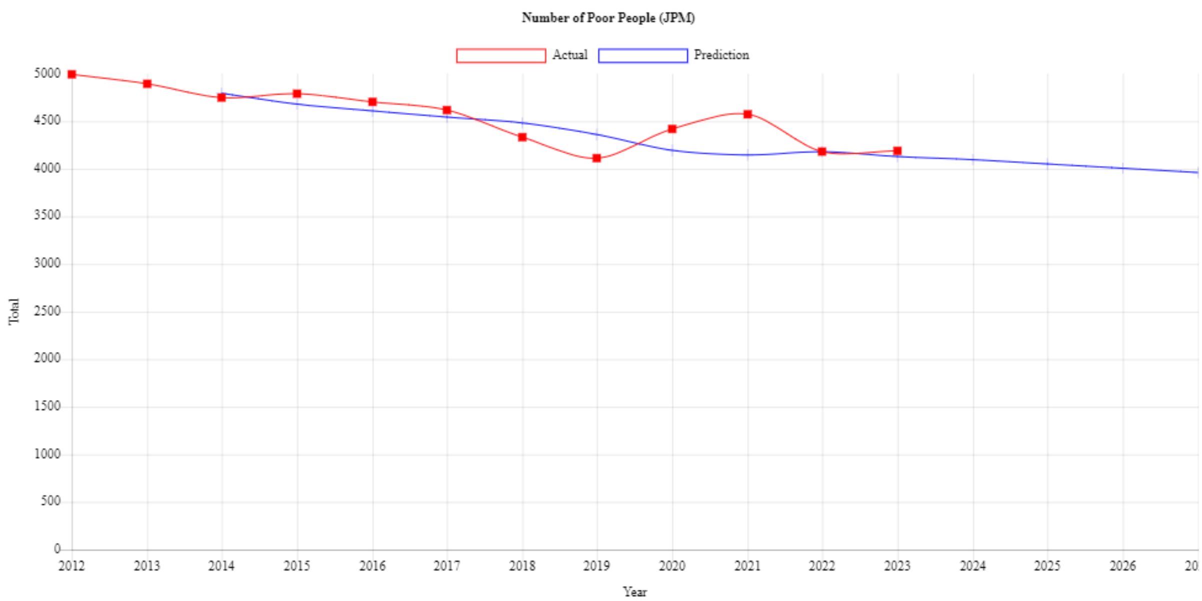

Fig. 8. JPM prediction results using MAPE to determine the optimal α and β parameters

To provide more context and support for these conclusions, we use the HDES model to show the performance of each prediction result for the following few years from the five categories of poverty data. To achieve this, we utilize the MAPE to determine the optimal parameters on Table 4.

Table 4. Prediction results are based on determining optimal parameter values by MAPE

Poverty and Inequality	HDES			
	2024	2025	2026	2027
P1	1.63	1.61	1.60	1.58
P2	0.38	0.38	0.38	0.38
GK	485141	504008	522875	541742
JPM	4618.5	4568.1	4517.7	4467.3
PPM	11.55	11.41	11.27	11. 13

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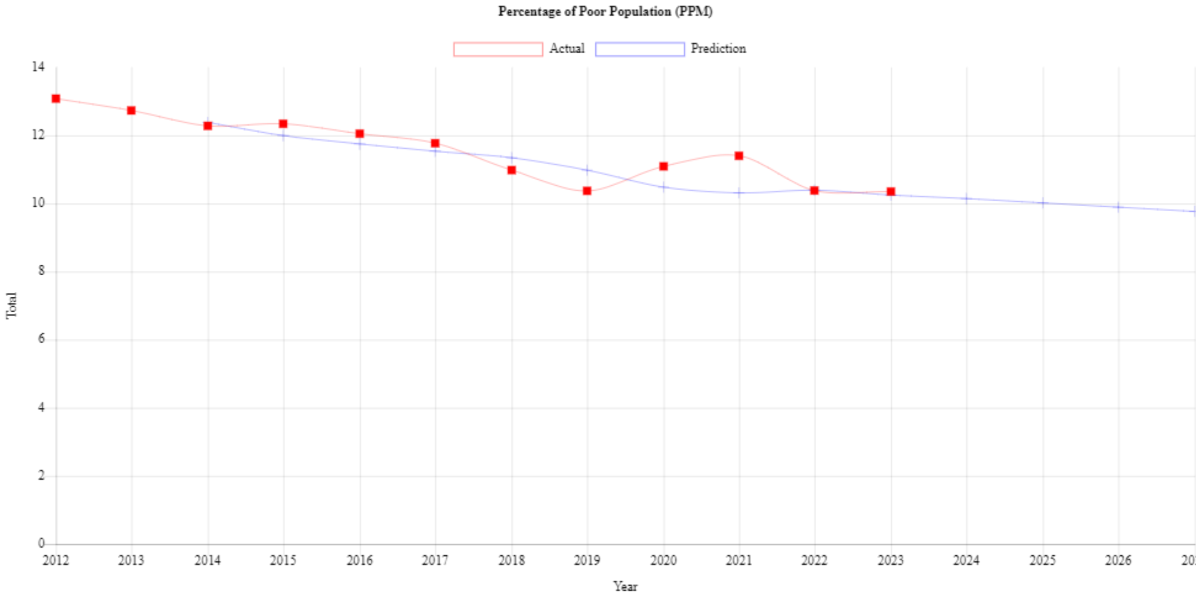

Fig. 9. PPM prediction results using MAPE to determine the optimal α and β parameters

Table 5. Prediction results using the SES model approach

Poverty and Inequality	SES			
	2024	2025	2026	2027
P1	1.63	1.63	1.63	1.63
P2	0.37	0.37	0.37	0.37
GK	524000	540700	557400	574100
JPM	4190	4192	4193	4195
PPM	10.34	10.34	10.34	10.34

Table 6 Prediction results using the ARIMA model approach

Poverty and Inequality	ARIMA			
	2024	2025	2026	2027
P1 (ARIMA (1, 1, 1)	1.62	1.62	1.62	1.62
P2 (ARIMA (0, 1, 1)	0.38	0.38	0.38	0.38
GK (ARIMA (1, 1, 1)	500593	515814	530867	545802
JPM (ARIMA (1, 1, 0)	4615.15	4566.24	4521.21	4479.79
PPM (ARIMA (1, 1, 0)	11.53	11.40	11.28	11.16

Table 7. Prediction results using the ARIMA model approach

Poverty and Inequality	ANN			
	2024	2025	2026	2027
P1	1.63	1.61	1.59	1.57
P2	0.39	0.40	0.41	0.42
GK	495812	512789	528911	545123
JPM	4621.5	4578.9	4535.1	4490.8
PPM	11.55	11.42	11.29	11.17

3.1. Model performance comparison

Based on the effectiveness of the HDES model's predictive outcomes, this section examines the performance of the SES, ARIMA, and ANN models (see Tables 5-7), utilizing the MAPE evaluation findings on Table 8. This provides a comparative analysis of the performance of each method.

Table 8. Comparative Analysis of Methods and Significance

Poverty and Inequality	MAPE				Significance
	SES	ARIMA	ANN	HDES	
P1	1.65	1.58	1.25	1.50	Excellent
P2	2.85	2.92	2.80	2.75	Excellent
GK	2.50	2.22	2.01	2.11	Excellent
JPM	2.55	2.37	2.25	2.30	Excellent
PPM	2.45	2.36	2.15	2.25	Excellent

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Table 8 presents the mean absolute percentage error, categorized into a specific significance range, to assess the accuracy of the forecasts [53]. Utilizing the MAPE approach, as illustrated in Table 2, requires that forecasts be substantial to avoid complications in assessing the accuracy of the measurements relative to the magnitude of the prediction.

4. Conclusion

Using the HDES statistical model, the goal of this study was to establish an online web-based prediction system that can forecast the number of poor families in East Java eligible for social food assistance in terms of five data categories: P1, P2, GK, JPM, and PPM. This study's geographical scope is confined to East Java, and the data timeframe is restricted to 2012–2023, focusing on univariate analysis without external influences, and with comparisons limited to SES, ARIMA, and ANN models.

If used correctly, the developed prediction system will automatically provide early information on the quantity of the five types of poverty data for the upcoming few periods, thereby supporting existing stakeholders in their decision-making. Specifically, this applies to the budget allocation plan, which allocates measurable funds and determines the number of low-income households eligible for social food assistance. Due to its dynamic nature, the prediction system can adjust to modifications in the available data.

This study applies statistical methods to create a TS prediction model with HDES. The average forecasting results from the five categories of poverty data indicate a mean absolute percentage error of less than 10%. For P1, P2, and GK, the results were, respectively, 1.50%, 2.75%, and 2.11%, while JPM and PPM recorded values of 2.30% and 2.25%. Table 8 demonstrates the highly satisfactory performance of the prediction algorithm in this system, underscoring its significance. ANN has consistently shown superior performance, yielding the lowest MAPE values across all variables. Artificial intelligence models, such as ANN, are able to more effectively capture the nonlinear patterns and relationships in the data.

The HDES and ARIMA models also exhibited commendable performance, with MAPE values slightly above those of the ANN model. This suggests that, despite nonlinear patterns, the linear trend in the data is sufficiently dominant for these models to make accurate predictions. The SES model exhibited the poorest performance among the four. This is expected, given the SES approach is incapable of capturing trends, whereas the data clearly indicates higher trends in GK and declining trends in JPM and PPM.

The ANN approach remains the optimal solution for precise forecasting, as it constantly surpasses other models. Nevertheless, for more straightforward and interpretable models, HDES or ARIMA serve as excellent alternatives, offering consistently high precision. Future research should evaluate the model using national-level statistics, broaden comparisons with more sophisticated forecasting techniques, integrate socio-economic variables such as inflation and food prices, and enhance the web-based system with additional interactive functionalities for policymakers.

Author Contributions

M. Masrur: Conceptualization, funding acquisition, methodology, project administration, resources, supervision, writing – original draft, writing – review & editing. S. Solikhin: Conceptualization, data curation, formal analysis, methodology, software, validation, writing – original draft, and writing – review & editing. M. W. S. Churum: Visualization, writing – original draft, and writing – review & editing. M. Z. Abdillah: Formal analysis, investigation, software, supervision, validation, and visualization. T. W. A. Putra: project administration and supervision.

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Declaration of Competing Interest

The authors of this study declare no personal or financial conflicts of interest that could have affected the results.

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