Comparative Study of Machine Learning and Holt-Winters Exponential Smoothing Models for Prediction of CPI's Seasonal Data

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***Abstract*— Inflation is one of the factors influencing price stability. Inflation affects people's purchasing power and impacts their decisions as economic actors. Consumer Price Index (CPI) is one of the factors used by economists to measure the inflation or deflation in a country. This research focuses on comparing the prediction results of the CPI for the Education Goods and Services using the Holt's Winters Exponential Smoothing and Machine Learning Methods, namely Long Short-Term Memory (LSTM), Extreme Learning Machine (ELM), Ridge, and Least Absolute Shrinkage and Selection Operator (LASSO). The data used is univariate data on the CPI for the Education Goods and Services in Malang City in 1996-2013, which was obtained from the publication of the Statistics Indonesia (BPS), entitled "Malang City in Figures" which was published in 1997-2014. The results of this research show that the Ridge Method produces the smallest Mean Absolute Percentage Error (MAPE) value compared to other Machine Learning Methods and the Multiplicative Holt-Winters Exponential Smoothing Method, with MAPE=2.10723%%. Machine Learning models that have been simulated have very good accuracy values, with MAPE values < 10%. Therefore, it can be assumed that the simulated Machine Learning models can make very good predictions on time-series data with seasonal patterns.**

Keywords—machine learning, data mining, time series, seasonality, consumer price index

I. Introduction

Historical data usually consist of series of observed data collected within particular time interval. The series are known as 'time-series' [1]. Time series data is usually ordered in time and time-dependent with certain trends or seasonal patterns. The data trends and patterns can be analyzed to predict the occurrence in the future. Time series data may have fluctuations or patterns which are repeated with fixed frequencies. This is called seasonality of time series data.

Inflation is one of the factors that influences price stability. According to the Statistics Indonesia (BPS), inflation is a tendency to increase the prices of goods and services in general which occurs continuously [2]. Inflation also affects people's purchasing power and impacts their decisions as economic actors. CPI is one of the factors used by economists to calculate the inflation rates. The CPI is an index number that measures the price of goods and services that are always used by consumers or households [3]. This is one of the indicators used to see monetary success in controlling inflation. The value indicates the occurrence of inflation or deflation in a country. CPI is used for several types of goods and services, one of which is educational goods and services.

Forecasting the CPI is carried out using time series analysis. The CPI is an index number that measures the price of goods and services in a country that always be utilized by consumers [4]. The method commonly used in forecasting time series data for the CPI is time series analysis methods, such as Moving Average and Double Exponential Smoothing. Lestari and Darsyah in their research proved that the Holt's Exponential Smoothing Method, which is a variant of Double Exponential Smoothing, produces MAPE, Mean Absolute Deviation (MAD), Mean Squared Deviation (MSD) values that are smaller than those produced by the Moving Average Method [4]. In another study conducted by Rosdianawati and Surjanto, it obtained that the Multiplicative Holt-Winters Exponential Smoothing Method which uses level, trend and seasonal equations produces better accuracy than Holt's Exponential Smoothing method which only uses level and trend equations [5]. From this research, it was revealed that CPI data is more suitable for analysis using methods that are able to analyze time series data with seasonality.

Another method applied to forecast time series inflation rates is Machine Learning. According to Pant, Machine Learning can be used to build an early warning system for the government so that it can produce decisions based on

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valid information to adjust existing monetary policy in a country [6]. Therefore, further studies that discuss the application of Machine Learning to predict inflation rates are important.

One of the studies on inflation prediction systems using Machine Learning was carried out by Almutairi [7]. The research discussed the application of Machine Learning algorithms for time series inflation forecasting. This model produced good accuracy, namely Root Mean Squared Error (RMSE) = 0.43600. In another research conducted by Narmandakh, a comparison was made of the performance of the Ridge and LASSO methods as types of Machine Learning methods with the classic Auto-Regressive (AR) time-series method for predicting inflation in Mongolia [8]. The results told that the performance of these Machine Learning methods is better than the AR method. Apart from that, another research conducted by Alfiyatin et .al also showed the good performance of Machine Learning Algorithms for forecasting inflation rates [9]. The model with the Extreme Learning Machine, which is a type of Machine Learning Algorithm based on Artificial Neural Network (ANN), produces good accuracy with an RMSE value = 0.02020.

This research focuses on comparing the prediction results of the CPI for the Education Goods and Services which is time series data using the Holt-Winters Exponential Smoothing and Machine Learning Methods. Holt-Winters Exponential Smoothing is one of the common methods used in prediction of time series data with seasonality. The Machine Learning Methods compared in this research are ELM, LSTM, Ridge, LASSO. The data taken as input is CPI for the Education Goods and Services in Malang City.

II. METHOD

This research has the purpose to compare the Holt-Winters Exponential Smoothing method with Machine Learning methods in forecasting the CPI for the Education Goods and Services in Malang. Holt-Winters Exponential Smoothing is a time series analysis method with level, trend and seasonal equations. The Machine Learning methods discussed include those based on ANN and Linear Machine Learning Methods.

A. Holt-Winters Exponential Smoothing

This method is able to handle time-series data containing levels, trends, as well as seasons. The algorithm utilizes 3 smoothing constants, smooths the time series data and uses them for predicts the future condition [10]. The smoothing constants used in this method are levels, trends, and seasonal smoothing constant. Thus, this method is also called Triple Exponential Smoothing.

The equations used in Holt-Winter's Exponential Smoothing method are:

Level smoothing:

$$L = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (1)$$

Trend smoothing:

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

Seasonal smoothing:

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \quad (3)$$

Forward forecasting:

$$F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (4)$$

With:

Y_t = actual data in t period
L_t = level estimation
b_t = trend estimation
S_t = seasonal estimation
α = smoothing constant for level estimation
β = smoothing constant for trend estimation
γ = smoothing constant for seasonal estimation
s = season length
m = number of forward forecasting
F_{t+m} = forecasting value of m forward period

B. Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM) is one of ANN-based Machine Learning Methods. ELM uses 1 hidden layer and can produce a faster learning process. The advantage of ELM is that there is no iteration, results in this algorithm converges much faster than traditional algorithms. There are several implementations of this algorithm, such as prediction and classification.

C. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is one of ANN-based Machine Learning algorithms, commonly used in supervised learning. This algorithm is a refinement of RNN. The advantage of using this method is that the hidden layer has memory cells with input gates, output gates, and forget gates in them [11]. This algorithm can handle the gradient missing problem in the RNN and produces better accuracy.

D. Ridge

Ridge, first introduced by Hoerl and Kennard, is a popular prediction method. This method is an improvement of Linear Regression [12]. The minimization problem for Ridge Regression, is:

$$\beta^{ridge} = \arg\min\left[\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=0}^{p} x_{ij}\beta_j\right)^2 + \lambda\sum_{j=1}^{J}\beta_j^2\right] \quad (5)$$

With:

β^{ridge} = ridge estimator
y_i = i-th dependent variable
β_0 = constant
β_j = coefficient of j-th independent variable
x_{ij} = independent variable
N = the amount of observations
p = the amount of independent variables

E. Least Absolute Shrinkage and Selection Operator (LASSO)

This method is applied to estimate the relationship between variables and make predictions based on the relationship. Least Absolute Shrinkage and Selection Operator (LASSO) is a regularization algorithm introduced by Tibshirani in 2016 [8]. This is similar to Ridge with adjustments to the penalty value calculated based on the coefficient's absolute value.

The minimization problem of LASSO is:

$$\beta^{lasso} = \arg\min\left[\sum_{i=1}^{N}\left(y_i - \beta_0 - \sum_{j=0}^{p} x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{J} |\beta_j|\right] \quad (6)$$

With:

β^{lasso}	= LASSO estimator
y_i	= i-th dependent variable
β_0	= constant
β_j	= coefficient of j-th independent variable
x_{ij}	= independent variable
N	= the amount of observations
p	= the amount of independent variables

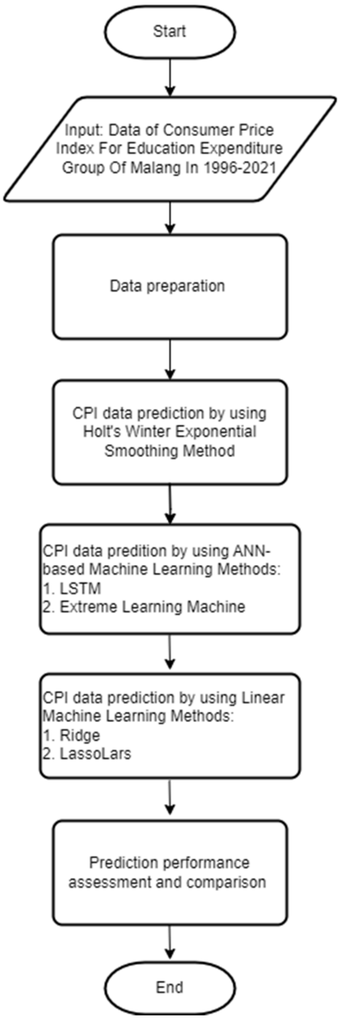

Fig. 1. Experiment Steps of The Research.

F. *Data and Methodology*

This research focuses on comparing the prediction results of time series data with seasonality by using the Multiplicative Holt's Winters Exponential Smoothing and Machine Learning Methods. The case discussed in this study is CPI for the Education Goods and Services. The Machine Learning Methods used are LSTM, ELM, Ridge, and LASSO. In this research, univariate data on the CPI for the Education Goods and Services in Malang City in 1996-2013 are used. The data was obtained from the publication of the Statistics Indonesia (BPS), entitled "Malang City in Figures" published in 1997-2014. The experimental stages in the research carried out are explained in Fig 1.

Based on the flow chart in Fig. 1., this research was carried out in several stages. First, data collection was carried out from data sources from the Statistics Indonesia (BPS) which can be accessed from https://malangkota.bps.go.id/. The data collected is univariate CPI data for the Education Goods and Services in Malang City for 1996-2013. Second, the data collected needs to go through the preprocessing stage, which consists of data cleaning (cleaning up data that is incorrect or not in accordance with the format), normalizing the data using the Z-Normalization Method, as well as splitting the entire data into training and testing data (67% for training data and 33% for testing data). The Januari 1996-Januari 2008 are included in training data, while the rest are included in testing data.

The next stage is the prediction of the CPI for the Education Goods and Services using several prediction models, as in TABLE I to TABLE V.

III. Results and Discussion

The data used in this research is CPI For Education Goods and Services data in Malang City in 1996-2013. Data is taken every month and 217 rows of data are obtained. This data is visualized in the graph in Fig. 2.

The graph in Fig. 2. explains that the monthly CPI For Education Goods and Services data has had a downward trend since 1996-2013. Apart from that, it also shown that the data has a seasonal pattern of increases every June-September in every year.

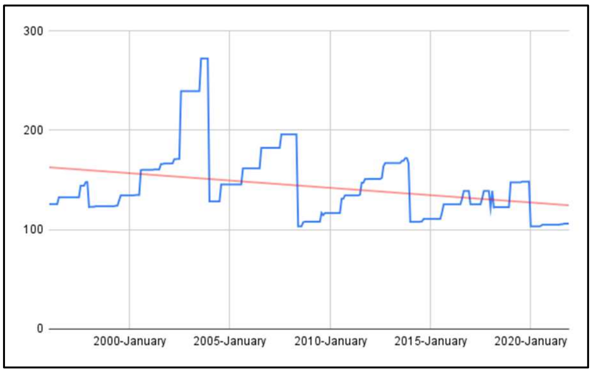

Fig. 2. Monthly CPI For Education Goods and Services of Malang In 1996-2013.

TABLE I. Multiplicative Holt-Winters Exponential Smoothing Model

Parameter	Nilai Parameter
Level Constanta (α)	0.15
Trend Constanta (β)	0.2
Seasonal Constanta (γ)	0.1
Season Length (s)	12
Number of Data Input Row	205
Number of Test Data Row	12

TABLE II. Extreme Learning Machine Model

Parameter	Nilai Parameter
Input nodes	12
Hidden nodes	12
Output nodes	1
Activation function	Sigmoid

TABLE III. LONG SHORT-TERM MEMORY MODEL

Parameter	Nilai Parameter
Input nodes	12
Hidden layers	2
Hidden nodes	2
Output nodes	1
Activation Function	Hyperbolic Tangent

TABLE IV. LASSO MODEL

Parameter	Nilai Parameter
Alpha (α)	0.01
Training Data	67%
Testing Data	33%

TABLE V. RIDGE MODEL

Parameter	Nilai Parameter
Alpha (α)	0.5
Training Data	67%
Testing Data	33%

TABLE VI. MAPE AND RMSE VALUE OF MODELS SIMULATED

No.	Methods	MAPE (%)	RMSE
1.	ELM	5.69090%	6.96955
2.	LSTM	2.50119%	4.69093
3.	LASSO	2.22390%	3.70859
4.	Ridge	2.10723%	3.60655
5.	Holt's Double Exponential Smoothing	3.79950%	8.34920
6.	Multiplicative Holt-Winters Exponential Smoothing	2.29919%	5.89187

In the experiment, the data obtained became inputs for forecasting systems carried out using the Holt-Winters Exponential Smoothing, ELM, LSTM, Ridge, and LASSO methods. The assessment result of each simulated model presented in TABLE VI.

TABLE VI shows that the model with the lowest MAPE and RMSE value is Ridge Model, with MAPE=2.10723% and RMSE=3.60655, followed by LASSO with MAPE=2.22390% and RMSE=3.70859. Both has smaller MAPE value compared to models with Multiplicative Holt-Winters Exponential Smoothing method. The ANN-Based Machine Learning Model with the lowest MAPE and RMSE value is the LSTM Model, namely with a MAPE=2.50119% and RMSE=4.69093.

A. Holt-Winters Exponential Smoothing

Fig. 3. contains a comparison graph between the predicted results from the Holt-Winters Exponential Smoothing Model and actual data. As seen in the graph, the predicted value can follow the increasing trend of the actual data.

B. ANN-Based Machine Learning

Fig. 4. shows a graph comparing the prediction results of the ANN-based Machine Learning Model, that is the ELM and LSTM Model with actual data. It can be seen in the picture that the prediction results with both models can follow the movement of the actual data which is up and down, as well as following the increasing trend of the actual data.

C. Linear Machine Learning

Fig. 5. shows a comparison of prediction results using the Linear Machine Learning, Ridge and LASSO methods with actual data. From this graph, it can be seen that the prediction results using the Linear Machine Learning Method can follow the movement of the actual data which goes up and down. However, the Ridge Method produces better (lower) MAPE values than the LASSO Method. Also, based on the simulation, all Linear Machine Learning models produce the lowest MAPE and RMSE value amongst all models were simulated.

All of the Machine Learning Models simulated produce very low MAPE values, below 10% (very good accuracy). Thus, the simulated Machine Learning models can make very good predictions on time-series data with seasonality.

IV. CONCLUSION

The focus of this research is to compare the prediction results of the Multiplicative Holt-Winters Exponential Smoothing method with Machine Learning for CPI For Education Goods and Services data, that belongs to time-series data with seasonal pattern. From the experiments that have been carried out, it can be concluded that the model using the Ridge Method produces the smallest MAPE and RMSE value, smaller than other Machine Learning Methods and the Multiplicative Holt-Winters Exponential Smoothing Method, in which MAPE=2.10723%% and RMSE=3.60655. Machine Learning models that have been simulated have very good accuracy values, with MAPE values < 10%. Thus, it can be said that the simulated Machine Learning models can make very good predictions on time-series data with seasonality.

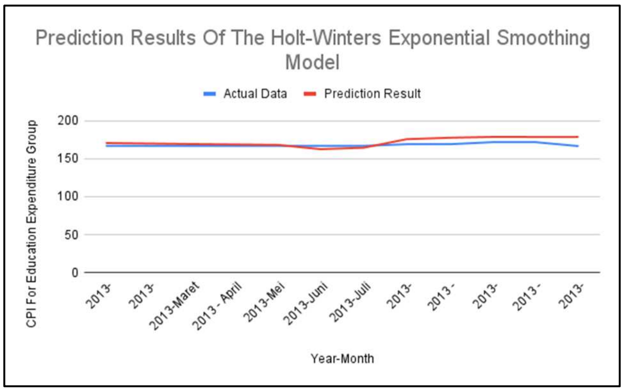

Fig. 3. Prediction Results of The Holt-Winters Exponential Smoothing Model.

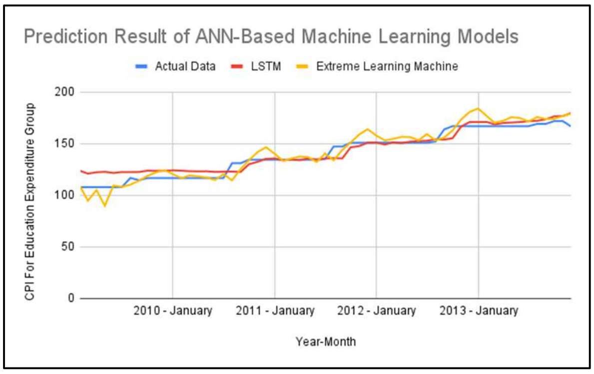

Fig. 4. Prediction Results of ANN-Based Machine Learning Models.

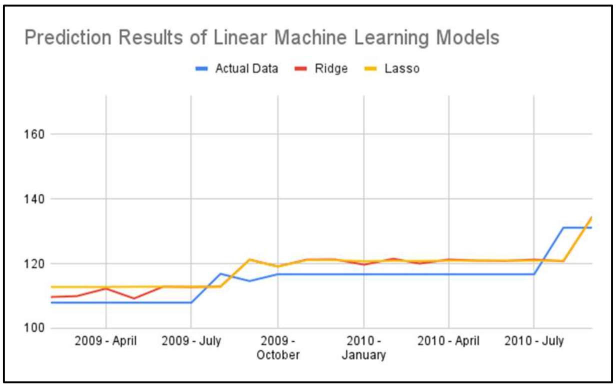

Fig. 5. Prediction Results of Linear Machine Learning Models.

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