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Artificial Neural Network Prediction Model for Agricultural Commodity Production Using Backpropagation Algorithm

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A B S T R A C T

The development of Artificial Intelligence (AI) technology has been widely used by the Government and Society to support daily activities, including supporting the decision-making process. In Indonesia's agricultural sector, innovations are currently being implemented using Machine Learning methods, especially Artificial Neural Networks, to estimate the yield of an agricultural commodity. This technology is very relevant to be applied in the agricultural sector, especially since the majority of Indonesians are farmers. With prediction of production and prices, the Government can estimate the amount of production and immediately set a strategy to keep prices stable. The use of predictive data on agricultural production results is very important in maintaining food availability and preventing price fluctuations that affect society. This study uses data on chili commodities, employing a qualitative method with the Backpropagation Algorithm of Artificial Neural Networks. The objective is to generate projections of the Artificial Neural Network (ANN) model using the Altair AI Studio with minimal error so that better prediction values and performances are produced. Based on the results obtained, the best network architecture is the 12-25-1 model for large chili production, and 12-15-1 for bird's eye chili pepper. This model is proven to be able to help production planning, supply distribution arrangements, and maintain price and supply stability by related agencies.

1. Introduction

Indonesia is known as a country with abundant natural resources, where most of its population relies on farming for their livelihood [1]. The agricultural sector is currently vital as part of the food security program initiated by the Government. To ensure the precise quantity of agricultural commodities needed to improve citizens' welfare, innovations are crucial to help farmers market their produce [2]. The development of Artificial Intelligence technology can now offer solutions to predict future harvests through artificial neural network machine learning [3]. Making predictions is a complex challenge often categorized as pattern recognition, which is highly suitable for resolution using the Artificial Neural Network (ANN) approach [4]. This technology can be applied in various fields, including agriculture [5]. In the agricultural sector, the amount of production is closely related to market prices. This is because it also impacts farmers' livelihoods, the needs of the community, the sustainability of the market's balance chain, the basis for macroeconomic calculations, tax rate determination, and so forth [6]. Determining market price predictions, especially during harvest, is crucial for deciding whether the harvest should be sold immediately or stored. However, this decision isn't uniform for all farmers. Farmers dealing with agricultural commodities prone to spoilage must, of course, make immediate decisions [7]. The Government's role is to control, supervise, and assist farmers and the community by providing guaranteed market price certainty, preventing farmers from incurring losses, particularly during harvest [8]. One such perishable commodity is chili, which includes large red chili, large green chili, and bird's eye chili pepper [9].

One important areas in the agricultural sector that receives special attention is the food and horticulture subsector [10]. Among horticultural commodities, chili is one of the main priorities in efforts to increase the growth of the agricultural sector [10]**.** Chili is a very popular consumption ingredient in Indonesia. The Ministry of National Development Planning of the Republic of Indonesia (Bappenas) noted that in 2023, the consumption of large chilies by the Indonesian people reached an average of 2.42 kilograms per capita per year, increasing by 4.3% compared to the previous year, and recording the highest figure in the last five years [11]. Meanwhile, bird’s eye chili pepper consumption also showed an increase of 5.8% (year-on-year/yoy), to 2.19 kilograms per capita per year, which is the highest amount since 2019. In total, the national demand for large chilies for household consumption in 2023 reached 675 thousand tons per year, a growth of 5.7% (yoy) compared to the previous year. Meanwhile, the demand for bird’s eye chili pepperfor household consumption also increased by 6.9% (yoy) to around 610.8 thousand tons per year [12]. Prayitno, in his research, argued that chili is a horticultural commodity that is highly sought after by the public [13]. The price of chili is relatively unstable because it is highly dependent on the availability of supply in the market [14]. When the stock of red chili is abundant, prices tend to fall; conversely, if the supply is limited, prices can increase sharply. According to Loanga and colleagues, the price of chili is influenced by five variables: the price of bird’s eye chili pepper for farmers, the price of bird’s eye chili pepper for traders, the amount of bird’s eye chili pepper production, the amount of demand for bird’s eye chili pepper, and the price of curly chili [12].

The price level of large red chili, both among producers/farmers and consumers, is highly dependent on the volume of production available [10]. Therefore, the active role of the regional government through related agencies is very necessary, especially through policies that support increased production and stabilization of chili prices. One of the recommended steps is the development of planting patterns and chili cultivation management aimed at meeting demand, especially when there is a decrease in supply [15]. Chili prices tend to fluctuate due to several factors, such as unstable distribution resulting from overproduction and underproduction [16]. Under Law No. 18 on Food, the Government has guaranteed that its role in the agricultural sector includes maintaining market price stability [17].

Referring to Law Number 23 of 2014 on Regional Government, regional governments are responsible for regulating food sector affairs, including the provision, distribution, and control of the supply stability and prices of staple foods in their respective regions [18]**.** One of the initiatives carried out to ensure the needs of the community, especially economically vulnerable groups, is the market operation program, which aims to keep prices stable [11]. Market operations are carried out by setting prices below market prices as an effort to increase the availability of goods through cooperation with private business entities, State-owned enterprise (BUMN), or direct distribution to retailers. The goal is to prevent excessive price spikes. The chili price prediction strategy has begun to be implemented in several regions in Java, for example, in Central Java Province [6]. Central Java Province is one of the largest chili-producing provinces in Indonesia, second only to East Java [19].

Table 1. Production of Bird's eye chili pepperand Large Chili in Indonesia in 2025 [19]

Province	Bird's eye chili pepperProduction (quintal)	Large Chili/TW/Teropong Production (quintal)
Aceh	640914,66	37287
North Sumatra	835826,84	29484,74
West Sumatra	279213,69	2,26
Riau	62856,38	11396,1
Jambi	435784,76	11156
South Sumatra	89483,57	66037,9
Bengkulu	242079,1	296531,85
Lampung	113333,83	59865,1
Bangka Belitung Islands	60092,78	
Riau Islands	14873,67	4496,84
Jakarta	404,15	1,2
West Java	1637558,85	1441340,45
Central Java	2480795,12	404419,36
Special Region of Yogyakarta	290844,06	11041,3
East Java	5689752,04	818452,1
Banten	26571,26	2841,89
Bali	220725,81	76145,64
West Nusa Tenggara	941552,26	104445,36
East Nusa Tenggara	112664,23	12829,41
West Kalimantan	98363,93	24415,39
Central Kalimantan	40374,9	7773,67
South Kalimantan	125753,72	81930,35
East Kalimantan	60583,26	8615,48
North Kalimantan	66463,29	54061,85
North Sulawesi	132955,76	228,5
Central Sulawesi	229180,07	25464,89
South Sulawesi	361279,04	161909,47
Southeast Sulawesi	38908,56	16230,29
Gorontalo	103720,4	
West Sulawesi	32753,37	23507,01
Maluku	39403,19	4373,9
North Maluku	40166,11	305
West Papua	12905,21	1182,73
Southwest Papua	33249,84	1232,79
Papua	9057,6	3758,8
South Papua	15568,31	2474,38
Central Papua	33738	14533
Papua Mountains		
Indonesia	**15649751,62**	**3819772**

The development of Artificial Intelligence (AI) technology, especially machine learning through artificial neural networks, has successfully mapped calculations into predictions [20] which are able to produce numbers or values of the next harvest, mapping the amount of harvest according to their needs, so that the government can help farmers in distributing agricultural commodity needs throughout Indonesia and even be able to export abroad so that farmers and the public do not need to worry about the rising and falling of market prices [6].

The use of Machine Learning (ML) technology enables computer systems to learn from data and experience to complete specific tasks independently [21]. This approach differs from traditional programming methods, which require explicit writing rules and procedures [22]. Machine Learning works through algorithms developed to detect patterns in data, then use those patterns to make predictions or decisions [23]. Research shows that Machine Learning (ML) and Deep Learning (DL) methods show superior performance compared to classical statistical approaches such as linear regression, especially in the context of predicting agricultural yields at the regional level [24][25]. One of the prominent techniques in Machine Learning is the Artificial Neural Network (ANN) [26], which is very effective in processing large-scale data and non-linear patterns. Artificial Neural Network (ANN) is an information processing model inspired by the workings of the human nervous system [4]. This model is capable of learning complex relationships between input and output data and recognizing hidden patterns that are not easily detected by conventional analysis techniques [24].

Prediction is a systematic process to estimate possible future events by utilizing historical data and current information, to minimize the error between actual results and estimates [27]. Forecasting agricultural commodities is an important step in overcoming problems faced by farmers as producers and society as consumers, especially related to price fluctuations such as chili commodities [12]. The use of artificial neural network technology is expected to overcome problems with crop production and can control the market prices of agricultural commodities in Indonesia [28].

2. Method

Research methodology refers to the steps or work structures that are followed systematically to achieve the expected research objectives [29]. This study applies a qualitative descriptive approach with a focus on data processing related to two types of agricultural commodities, that is large chili and small chili. The qualitative approach is used to obtain a thorough understanding of the phenomena experienced by the research subjects, through descriptive verbal narratives within their natural context, utilizing various scientific methods [30]. The data samples used in this study were processed using the backpropagation algorithm, using data sourced from official publications of the Central Statistics Agency (BPS) and information on agricultural production of chili commodities in Central Java Province, with a focus on test data for the harvest of large chili and small chili in Magelang Regency [19].

The Backpropagation algorithm will be used as the data analysis method using AI Studio software to project numerical outcomes, aiming for the highest accuracy and minimal data errors so that it can be seen that the algorithm function can run as expected [31].

2.1. Operational Concept

Operational concepts describe the indicators that are related in detail and measurably from a concept or dimension [30].

Table 2. Operational Concept

Method	Indicator	Instrument
Backpropagation Algoritm [21]	Numerical data of crop production: 1. Large Chili 2. Bird's eye chili pepper	1) Prediction data of chili plant production in Magelang Regency 2) Performance of Neural Network prediction model

2.2. Data Collection Sources and Techniques

This study uses primary data as its main source, obtained from agricultural horticulture statistics and official data from the Central Statistics Agency (BPS). For data collection, researchers conducted direct observations at the research location to identify research problems. This was followed by direct interviews with extension workers and farmers as part of the data collection process [32]. The data includes monthly production information for two types of chili, that is large red chili and bird's eye chili pepper from 2018 to 2024. This data is then classified by sub-district and chili type, allowing for specific analysis and recognition of chili plant production patterns. This information will form the basis for building a predictive model that considers differences between chili categories and production trends within each category.

Meanwhile, secondary data is supported based on information used to complement primary data[33]. This data was obtained through interviews with parties directly related to the chili production process in Magelang Regency, such as the Department of Agriculture, farmers, agricultural extension workers, and local communities.

2.3. Preprocessing Data

In the data preprocessing stage, the collected information is first validated by matching it against actual chili production data obtained directly from official sources, specifically the Magelang Regency Agriculture and Food Service. Preprocessing in other machine learning models requires finding outliers, which are data points that deviate before data validation is carried out [34]. This is, of course, done based on the conditions or forms of the existing data. This validation aims to check the consistency of the data and detect possible differences or discrepancies between the data downloaded from the Horticultural Agricultural Statistics Data Provision Information System (SIPEDAS) with the actual conditions in the field as data obtained through the Magelang Regency Agriculture and Food Service [35]. Preprocessing also involves a cleaning process, including removing duplicates and addressing missing values [36][29], followed by validation. After validation, the dataset is checked for abnormalities in the obtained dataset, such as missing values. If found, steps are taken to complete the missing data [28]. This ensures the prediction model can operate optimally without being disturbed by incomplete data [37]. Prediction criteria depend on the specific dataset collected based on research needs [38]. In addition, data format standardization is performed to ensure all variables are in a uniform and consistent numerical form [31]. This step helps prevent errors during the analysis and training process of the artificial neural network model [16]. Preprocessing follows a series of steps, beginning with the collection of data ready for processing [25][36].

Furthermore, the horticultural chili production data was transformed from a wide table format into a time series format for use in Artificial Neural Network (ANN) modeling with AI Studio. This transformation was carried out by sorting the data by time for each sub-district and chili category, such as large chili and bird's eye chili pepper [35].

To form a dataset that matches the time series prediction, the dataset used was obtained and then processed through a windowing process with a 13-month sliding window approach [39]. In this approach, each training iteration uses production data for the previous 12 months as input features, while the following 1 month is used as a prediction target. This method allows the model to recognize annual seasonal patterns in chili production and generate predictions based on historical trends in each sub-district.

In the final results, re-testing is performed to identify any errors in the data by analyzing the propagation algorithm until more accurate data is obtained [40]. Adjustments are made to the algorithm because, in real data in the field there is a tendency for extension workers not to fill in data in the production database; the architectural model is expected to be more accurate in producing predictions of production results.

2.4. Training of Artificial Neural Network Architecture Model

In the training stage of the Artificial Neural Network (ANN) architecture model, chili production data will be processed using the sliding window technique to form a set of training and testing data [41]. The model will be trained using a 13-month sliding window approach, where each iteration uses production data from the previous 12 months as input features and the next month as a prediction target. With this, the model can recognize seasonal patterns of chili production in each sub-district based on historical data. After the training process, an evaluation is conducted by comparing the predicted output with the actual production data to measure the model's performance [27]. This involves using data that has not been included in the training process to assess the model's performance [4].

This model is built using 12 neurons in the input layer, which represent chili production data for the previous 12 months, and 1 neuron in the output layer as the prediction target. To determine the best architecture, various model configurations were tested: 12-5-1, 12-10-1, 12-15-1, 12-20-1, 12-25-1, and 12-30-1, for both the large chili and the bird's eye chili pepper datasets.

After the best architecture was identified, the model was further tested with various numbers of training cycles: 500, 1000, 1500, 2000, 2500, 3000, and 3500. This testing aimed to evaluate the optimal number of training cycles that yielded the best performance in predicting chili production.

2.5. Model Testing and Evaluation

Each architecture was tested in stages, starting from a simple model (12-5-1) to a more complex model (12-30-1). This staged approach allows for performance comparison between configurations in terms of prediction accuracy and model efficiency [42]. Furthermore, once the optimal architecture was identified, the model was tested with varying numbers of training cycles to determine the optimal iteration that produced the most accurate predictions. For comparison, a regression algorithm was also used to evaluate the ANN's performance in handling chili production prediction, thus offering a clearer perspective on the superiority of the developed model [31].

The evaluation was performed by utilizing the performance operator in the Altair AI Studio software, which supports the statistical evaluation of regression tasks and generates various performance indicators [43]. Several metrics were used, including : Root Mean Squared Error (RMSE) [24], which measures the average prediction error. The smaller the RMSE value, the higher the accuracy of the model in predicting chili production [3]. Additionally, Mean Absolute Error (MAE) was used to calculate the average absolute difference between predicted and actual values, thus providing a direct measure of the model's accuracy level [23]. In this study, RMSE and MAE are the main metrics in assessing the overall level of accuracy of the prediction results. In addition, Correlation analysis was included to illustrate the linear relationship between the model's predictions and the actual data. A correlation value close to 1 signifies the model's strong ability to recognize data patterns, whereas a low correlation value suggests that the model is not optimal in capturing data trend patterns. All of these metrics provide an overview of the prediction error rate of each model architecture, making it easier to choose the most balanced and best model between accuracy and complexity [24].

In the implementation of the chili production prediction model based on Artificial Neural Network (ANN), several risks need to be anticipated to ensure its long-term sustainability. Firstly, policy changes in the agricultural sector can affect the production data reporting system used as the basis for model training. Furthermore, reliance on data presents a significant challenge, especially if the available data is incomplete, contains errors, or does not reflect actual conditions in the field [4]. This can impact the model's accuracy and its reliability in supporting decision-making. Then, the variability of field data due to external factors, such as extreme weather changes, disruptions in planting patterns, or fluctuating fertilizer prices, can lead to unpredictable shifts in production patterns [44]. This risk may reduce model

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performance in the long term, especially if the training data does not encompass sufficient variation. Therefore, the model must be updated regularly with the latest data to adapt to changing field conditions.

3. Results and Discussion

Artificial Neural Networks (ANN) excel at recognizing activity patterns based on previously learned historical data, enabling them to generate predictions for new, unseen data. This process is systematically included in the form of predictive computing [22]. The utilization of Artificial Neural Networks itself is part of the field of artificial intelligence in computer science. Artificial Intelligence (AI) offers various techniques and algorithms that allow automatic data analysis and processing [45], aimed at solving diverse problems, including through the Backpropagation method [35].

3.1. Backpropagation

The following are the stages in implementing the Backpropagation Algorithm: [46]

- Step 0: Initialize weights.
- Step 1: If the stopping condition is not met, the process proceeds to steps 2–9.
- Step 2: During the training process, the system will execute the procedure from steps 3–8.

Feedforward Stage

- Step 3: Each unit in the input layer receives an input value (xi, for i=1 to n).
- Step 4: Units in the hidden layer (zj, for j=1 to p) process the data by adding weights to the input received.

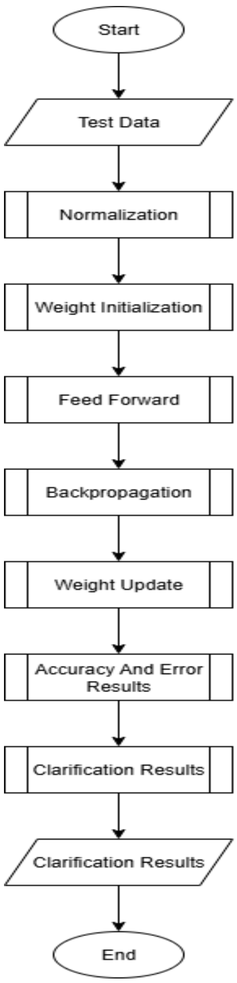


Figure 1. Backpropagation Flow [46]

In general, the data processing process using the artificial neural network method based on the backpropagation algorithm is divided into 3 stages, including [3] :

1) Data preprocessing
2) Training and modeling of artificial neural networks, and
3) Testing

3.2. Data preprocessing

The dataset consists of 2,520 time series entries with 22 attributes, which include one date attribute per month from 2022 to 2024, as well as 21 other attributes representing the amount of chili production in 21 sub-districts in Magelang Regency [47].

Table 3. Large chili data from 2022 to 2024 [14]

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	Tanggal	SALAM	BOROBU	NGLUW	SALAM	SRUMBI	DUKUN	MUNTIL	MUNGK	SAWAN(	CANDII	MERTC	TEMPUI	KAJORI	KALIANG	BANDON	WINDUSA	SECAN	TEGALI	PAKIS	GRABA(	NGABLAI
86	Jan-22	180,00	1050,00	74,00	568,00	1153,00	921,00	607,00	728,70	235,00	75,00	210,00	70,00	725,00	350,00	440,10	2415,00	2061,00	223,00	5046,00	11196,00	7651,00
87	Feb-22	189,00	980,00	140,00	770,00	960,00	2860,00	699,00	565,40	7210,00	210,00	280,00	151,00	1030,00	280,00	141,00	19810,00	690,00	194,00	5390,00	16344,00	6066,00
88	Mar-22	280,00	650,00	230,00	185,00	1200,00	4515,00	408,00	610,00	6020,00	280,00	0,00	152,00	994,00	1540,00	140,00	41300,00	560,00	0,00	12567,00	5626,00	6279,00
89	Apr-22	282,00	630,00	329,00	600,00	1050,00	4316,00	1190,00	431,00	4550,00	139,00	0,00	138,00	938,00	700,00	138,00	7371,00	195,00	0,00	11830,00	1781,00	7014,00
90	May-22	640,00	980,00	350,00	700,00	1120,00	3290,00	1431,00	490,00	4200,00	143,00	140,00	70,00	1050,00	2245,00	145,00	5970,00	910,00	0,00	705,00	3570,00	7630,00
91	Jun-22	260,00	265,00	225,00	180,00	982,00	3847,00	1401,00	295,00	940,00	180,00	132,00	64,00	1042,00	2898,00	169,00	2199,00	375,00	295,00	22719,00	4110,00	5320,00
92	Jul-22	245,00	602,00	126,00	250,00	1165,00	1206,00	514,00	193,00	1631,00	69,00	69,00	69,00	408,00	2027,00	99,00	7565,00	385,00	132,00	3658,00	4021,00	4414,00
93	Aug-22	240,00	120,00	329,00	130,00	1535,00	3261,00	611,00	429,60	1775,00	179,00	0,00	69,00	1030,00	2077,00	83,00	1483,00	511,00	128,00	3240,00	1870,00	6851,00
94	Sep-22	50,00	140,00	475,00	183,00	1503,00	4431,00	195,00	264,00	1088,00	130,00	0,00	0,00	1102,00	621,00	342,00	1336,00	599,00	97,00	4415,00	3369,00	6474,00
95	Oct-22	200,00	65,00	505,00	195,00	1086,00	3416,00	512,00	360,00	1540,00	63,00	65,00	0,00	1083,00	531,00	176,00	1019,00	326,00	98,00	4090,00	3171,00	6255,00
96	Nov-22	136,00	0,00	360,00	185,00	626,00	4490,00	756,00	245,00	1415,00	384,00	63,00	0,00	791,00	737,00	90,00	629,00	470,00	281,00	8320,00	3999,00	4302,00
97	Dec-22	213,00	0,00	102,00	380,00	584,00	1467,00	1089,00	174,00	366,00	112,00	0,00	0,00	283,00	714,00	231,00	643,00	428,00	112,00	765,00	4832,00	3189,00
98	Jan-23	129,00	1863,00	0,00	1070,00	1251,00	4441,00	1701,00	492,00	1725,00	450,00	0,00	0,00	265,00	1449,00	210,00	1397,00	898,00	252,00	3835,00	11425,00	5995,00
99	Feb-23	139,00	4969,00	0,00	1347,00	1492,00	5808,00	1130,00	340,00	1278,00	207,00	0,00	0,00	721,00	1268,00	145,00	8068,00	2763,00	490,00	5300,00	13428,00	7219,00
100	Mar-23	450,00	4536,00	69,00	3005,00	1488,00	5676,00	1052,00	325,00	7068,00	268,00	125,00	0,00	970,00	2278,00	131,00	25862,00	4720,00	142,00	37940,00	3406,00	6597,00
101	Apr-23	135,00	4969,00	291,00	670,00	646,00	5286,00	970,00	293,00	7156,00	128,00	0,00	0,00	976,00	1384,00	143,00	19793,00	2201,00	181,00	24510,00	3223,00	5854,00
102	May-23	649,00	4425,00	358,00	2655,00	634,00	4556,00	1886,00	162,20	1786,00	65,00	69,00	0,00	1027,00	531,00	121,00	10170,00	677,00	172,00	19510,00	1617,00	6108,00
103	Jun-23	195,00	2365,00	387,00	512,00	612,00	4895,00	2280,00	338,00	660,00	67,00	69,00	0,00	1072,00	2441,00	62,00	2517,00	129,00	110,00	11133,00	837,00	6190,00
104	Jul-23	243,00	670,00	330,00	946,00	601,00	2724,00	2491,00	196,00	1260,00	59,00	63,00	0,00	1419,00	607,00	123,00	1179,00	0,00	64,00	8968,00	938,00	5917,00
105	Aug-23	190,00	907,00	339,00	614,00	670,00	3018,00	2972,00	319,20	1239,00	52,00	53,00	0,00	1184,00	1550,00	86,00	545,00	0,00	154,00	10930,00	350,00	4402,00
106	Sep-23	281,00	235,00	459,40	677,00	858,00	771,00	1700,00	195,30	960,00	113,00	53,00	0,00	1334,00	1484,00	36,00	1093,00	0,00	78,00	6885,00	539,00	3332,00
107	Oct-23	188,00	222,00	420,60	1717,00	2494,00	3769,00	900,00	193,00	1320,00	252,00	43,00	0,00	2880,00	1538,00	87,00	621,00	0,00	179,00	7850,00	475,00	4575,00
108	Nov-23	357,00	210,00	351,00	2698,00	945,00	3633,00	546,00	290,00	999,00	131,00	43,00	0,00	2170,00	845,00	105,00	317,00	42,00	192,00	8042,00	623,00	1966,00
109	Dec-23	387,00	0,00	514,00	2380,00	2000,00	2818,00	655,00	292,00	1206,00	132,00	0,00	0,00	1890,00	0,00	129,00	941,00	58,00	101,00	6505,00	632,00	2149,00
110	Jan-24	186,00	1830,00	243,80	115,00	886,00	3962,00	640,00	156,60	1860,00	4,30	30,00	0,00	298,00	630,00	43,20	3253,00	4,20	120,00	6655,00	929,00	1556,00
111	Feb-24	149,00	1658,00	20,00	170,00	749,00	2728,00	445,00	200,60	2493,00	4,20	40,00	0,00	317,00	252,00	57,80	3751,11	0,00	129,00	6301,00	2353,00	1762,00
112	Mar-24	145,00	1743,00	259,50	1152,00	798,00	2695,00	552,00	198,90	3658,00	84,00	0,00	0,00	796,00	180,00	100,00	3682,00	0,00	94,00	15200,00	3239,00	2008,00
113	Apr-24	178,80	1811,04	237,40	1500,00	576,00	2837,00	283,00	282,90	3720,00	5,60	0,00	0,00	534,00	197,20	93,00	9457,00	19,85	43,00	25296,00	2760,52	2358,00
114	May-24	185,00	1685,60	105,00	120,00	560,00	2855,50	164,00	260,40	2782,00	22,90	0,00	0,00	593,00	248,00	121,10	15272,00	51,30	8,50	9498,00	2888,88	2260,00
115	Jun-24	166,00	1598,24	148,00	186,00	524,00	2866,50	260,00	279,80	2330,00	50,60	15,00	0,00	904,00	395,00	128,80	9033,00	252,10	33,00	7982,60	2711,80	2206,00
116	Jul-24	440,00	1606,00	149,40	129,00	722,00	4086,50	492,00	239,10	100,00	60,60	25,00	0,00	786,00	260,00	72,80	3637,00	110,70	0,00	7764,00	1746,46	1880,00
117	Aug-24	350,00	1734,00	147,00	1040,00	742,00	4077,70	710,00	180,40	120,00	57,50	10,00	0,00	632,00	265,00	56,00	3311,00	57,70	0,00	7949,60	2659,44	1470,00
118	Sep-24	234,50	1300,71	171,00	1302,00	834,00	3964,90	321,00	161,40	140,00	50,10	15,00	0,00	575,00	396,00	126,80	2773,13	24,70	32,00	7280,00	2573,95	1716,00
119	Oct-24	158,00	761,27	377,00	1796,82	744,85	5006,86	2950,08	159,44	1001,54	64,05	40,00	0,00	652,58	585,00	309,46	2600,00	8,57	108,86	7760,00	4228,00	1487,31
120	Nov-24	181,00	880,00	24,00	1604,00	920,00	2570,50	512,12	85,00	765,00	73,33	50,00	0,00	695,00	325,00	183,60	2125,00	0,00	124,00	4476,00	1544,15	1602,00
121	Dec-24	158,00	0,00	22,50	884,00	926,00	2626,00	781,00	94,00	590,00	89,33	65,00	0,00	605,00	455,00	152,20	2255,00	11,40	116,00	4314,00	2626,54	1741,00

Table 4. Large chili data from 2022 to 2024 [14]

	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	SALAM	BOROBU	NGLUW	SALAM	SRUMBU	DUKUN	MUNTILA	MUNGK	SAVANI	CANDIN	MERTC	TEMPU	KAJORAI	KALIANGK	BANDC	WINDUSAI	SECANG	TEGALF	PAKIS	GRABAG	NGABLAK
87	222,00	6510,00	500,00	1190,00	3088,00	4760,00	910,00	1024,80	4270,00	695,00	140,00	162,00	1321,00	210,00	392,10	4620,00	2829,00	2676,00	4220,00	20510,00	3246,00
88	210,00	6860,00	438,00	155,00	3640,00	7000,00	1080,00	907,30	4620,00	560,00	0,00	280,00	1125,00	1610,00	281,00	7150,00	1540,00	1400,00	10850,00	9100,00	3542,00
89	210,00	5250,00	560,00	1360,00	2870,00	5814,00	1050,00	910,00	2310,00	560,00	0,00	280,00	1201,00	2500,00	545,00	5670,00	1820,00	2120,00	10290,00	4550,00	3980,00
90	635,00	2870,00	700,00	1820,00	2660,00	5110,00	923,00	700,00	3475,00	630,00	70,00	280,00	1400,00	2660,00	350,00	3360,00	2975,00	2520,00	70,00	1965,00	4270,00
91	295,00	2275,00	355,00	440,00	2960,00	7431,00	409,00	570,00	1025,00	533,00	68,00	61,00	1151,00	2790,00	259,00	1316,00	530,00	1630,00	9024,00	4451,00	4206,00
92	232,00	0,00	398,00	501,00	2807,00	5413,00	610,00	682,60	2826,00	474,00	69,00	138,00	891,00	1393,00	245,00	1536,00	737,00	1431,00	3575,00	4629,00	2994,00
93	255,00	0,00	528,20	621,00	2882,00	6302,00	1113,00	785,50	2782,00	737,00	67,00	198,00	1063,00	1206,00	374,00	1890,00	575,00	1190,00	8780,00	3940,00	3432,00
94	245,00	0,00	472,20	1072,00	2804,00	7986,00	638,00	797,00	2546,00	610,00	0,00	70,00	1239,00	345,00	422,00	2364,00	475,00	1051,00	5575,00	4858,00	3815,00
95	185,00	1710,00	996,00	656,00	1949,00	4782,00	770,00	451,50	2288,00	341,00	68,00	129,00	1146,00	675,00	428,20	1147,00	431,00	702,00	3130,00	5584,00	5304,00
96	317,00	3603,00	783,00	448,00	3098,00	5891,00	558,00	529,00	3431,00	992,00	0,00	130,00	1135,00	1024,00	310,00	1048,00	234,00	1096,00	5705,00	12908,00	4075,00
97	150,00	120,00	770,00	1416,00	1614,00	5324,00	1187,00	268,00	419,00	365,00	53,00	29,00	374,00	414,00	450,00	1222,00	199,00	810,00	355,00	6706,00	3948,00
98	24,00	3350,00	732,00	2095,00	2960,00	17336,00	1863,00	399,00	629,00	1392,00	0,00	69,00	1169,00	276,00	345,00	2406,00	552,00	1733,00	1875,00	25411,00	4350,00
99	141,00	5626,00	514,00	2730,00	3202,00	9454,00	1180,00	418,00	1136,00	560,00	0,00	71,00	1176,00	1469,00	301,00	5133,00	994,00	2417,00	6705,00	22718,00	4748,00
100	821,00	4672,00	661,00	5898,00	3175,00	12562,00	1462,00	445,00	2653,00	1116,00	62,00	125,00	1197,00	2546,00	190,00	7890,00	2124,00	640,00	18995,00	8789,00	4835,00
101	146,00	4672,00	655,00	1843,00	2350,00	9714,00	895,00	424,00	1876,00	484,00	69,00	142,00	1440,00	1341,00	225,00	5704,00	2937,00	910,00	14260,00	6845,00	4780,00
102	895,00	4484,00	645,00	1386,00	952,00	7714,00	767,00	536,30	3072,00	531,00	69,00	167,00	1289,00	708,00	304,00	3205,00	3486,00	1166,00	14010,00	3771,00	5272,00
103	320,00	2095,00	533,00	3355,00	1906,00	6505,00	2848,00	552,00	2127,00	1003,00	66,00	130,00	1600,00	2903,00	336,00	1909,00	2077,00	944,00	5673,00	2680,00	5286,00
104	366,00	843,00	585,10	1526,00	1545,00	5906,00	3290,00	550,00	1270,00	444,00	59,00	63,00	2050,00	373,00	266,00	8898,00	896,00	639,00	4993,00	1591,00	5082,00
105	258,00	210,00	568,00	1938,00	1728,00	4765,00	2918,00	542,60	1298,00	584,00	54,00	59,00	2174,00	2148,00	90,00	1305,00	1508,00	673,00	4213,00	1125,00	3529,00
106	266,00	147,00	810,70	1169,00	1760,00	5373,00	1900,00	431,70	970,00	785,00	57,00	48,00	2038,00	1606,00	75,00	964,00	1620,00	304,00	5013,00	1137,00	3782,00
107	119,00	113,00	665,70	3339,00	2967,00	3382,00	1482,00	314,80	3259,00	635,00	49,00	117,00	2106,00	685,00	420,00	2174,00	867,60	455,00	5610,00	1910,00	2630,00
108	539,00	113,00	535,00	777,00	2194,00	4003,00	192,00	400,00	2905,00	648,00	52,00	103,00	2236,00	824,00	273,00	1848,00	503,00	1914,00	3000,00	1172,00	2430,00
109	299,00	0,00	910,00	4697,00	3770,00	4181,00	1476,00	399,40	3584,00	659,00	0,00	125,00	1805,00	0,00	184,00	2007,00	973,00	474,00	1755,00	1949,00	2188,00
110	122,00	2695,00	763,10	485,00	1936,00	4817,00	980,00	115,10	4730,00	21,00	30,00	11,00	477,00	3007,00	124,80	1081,00	1215,80	366,00	5805,00	4568,00	1467,00
111	122,00	2732,00	751,20	720,00	2098,00	4402,00	852,00	125,70	6229,00	12,85	80,00	17,00	1045,00	650,00	120,00	1612,00	1154,00	397,00	5345,00	6122,00	1679,00
112	149,00	2940,00	608,00	2400,00	2278,00	4589,50	781,00	139,60	6620,00	567,70	40,00	27,00	930,00	450,00	128,20	2151,00	1129,00	256,00	13342,00	6063,00	2000,00
113	198,00	3063,00	688,60	2760,00	1668,00	4990,00	872,00	280,80	5775,00	51,21	0,00	31,40	497,00	1109,20	218,30	7066,00	1375,80	477,00	18204,00	6067,00	2011,00
114	306,00	2644,40	488,00	1418,00	1255,00	8789,00	422,00	295,20	6468,00	108,96	0,00	438,00	704,00	480,00	192,70	10688,00	1459,20	346,00	11589,50	6035,62	4041,00
115	250,00	1193,11	512,00	255,00	1224,00	7782,00	325,00	310,36	3621,00	134,20	0,00	387,00	855,00	590,00	139,20	5352,00	1561,60	355,00	7719,00	5918,72	5558,00
116	650,00	1000,88	532,20	215,00	1542,00	8385,00	641,00	329,80	140,00	120,00	30,00	235,00	827,00	343,00	104,40	3055,00	1249,60	337,00	7192,00	5538,20	5836,00
117	720,00	1285,00	626,70	302,90	1416,00	8148,80	756,00	273,30	1310,00	115,00	50,00	172,80	854,00	630,00	127,60	3218,00	1367,80	247,50	3542,00	7098,60	5602,00
118	796,00	1270,00	929,20	1911,00	1682,00	7348,60	624,30	235,30	1582,00	128,30	35,00	199,00	862,00	384,00	261,00	2132,00	1259,30	410,00	4052,00	7416,98	6340,00
119	667,00	5832,39	206,41	4857,69	1601,28	9893,63	6768,20	490,90	2529,67	99,90	43,33	149,28	984,39	900,00	609,00	2548,66	1236,56	498,31	7465,71	9026,83	13415,32
120	731,00	1150,00	175,90	2836,00	1544,00	7024,36	808,61	143,50	2185,00	66,66	65,00	160,00	965,00	600,00	307,40	2152,00	1418,00	583,00	1440,00	5934,40	1844,00
121	753.00	0.00	175.90	2591.00	2121.00	5170.90	545.00	220.60	1785.00	126.66	75.00	110.00	932.00	450.00	458.20	6332.00	1424.00	587.00	1674.00	7580.36	2175.00

The data that has been collected and processed previously is then entered into the modeling using AI Studio. In this process, based on statistical analysis of the data in AI Studio as shown in the two figures below, several discrepancies were found in the data that needed to be adjusted before further analysis [43].

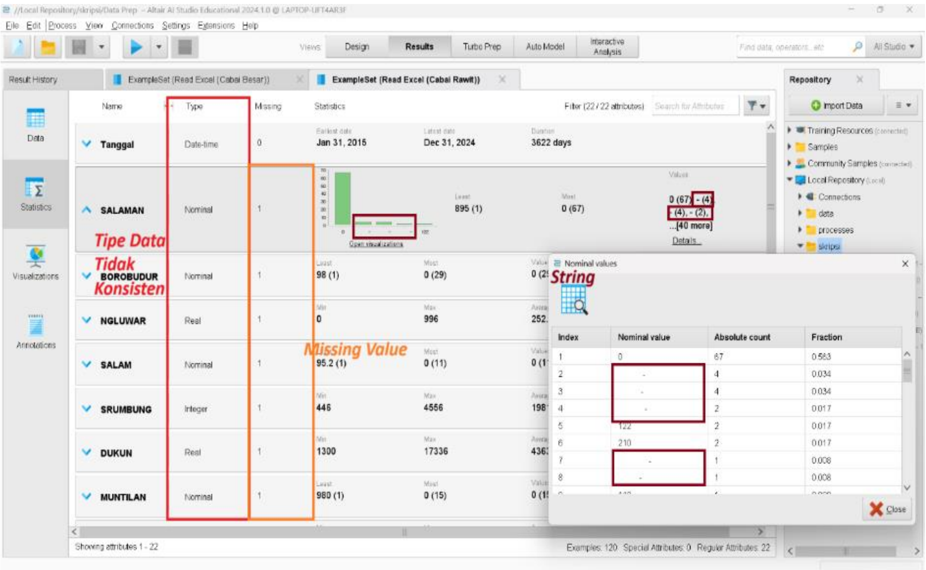
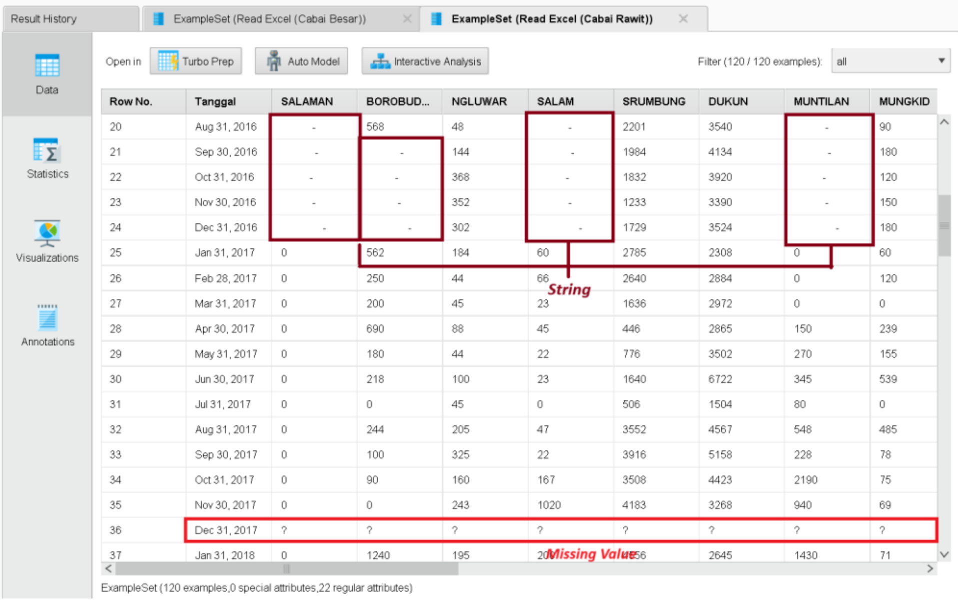


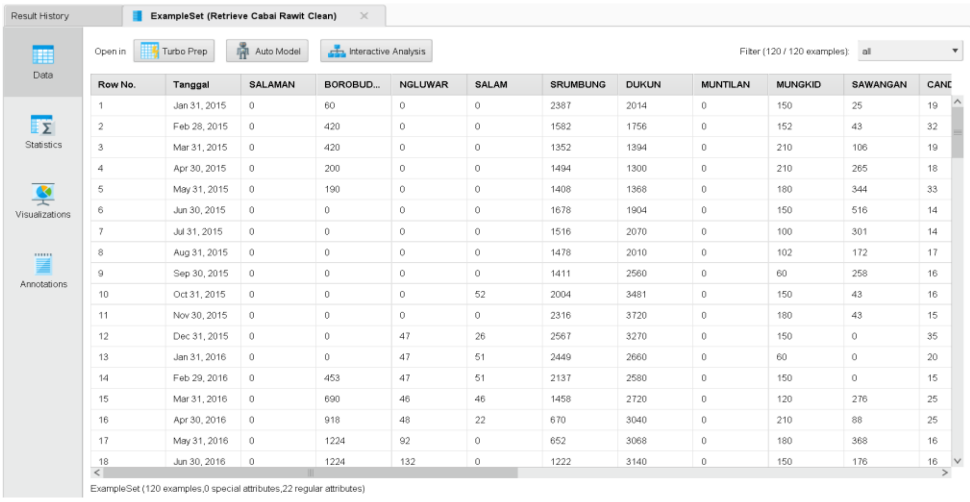
Figure 2. Identification of Discrepancies in Initial Data



Row No.	Tanggal	SALAMAN	BOROBUD...	NGLUWAR	SALAM	SRUMBUNG	DUKUN	MUNTILAN	MUNGKID
20	Aug 31, 2016	-	568	48	-	2201	3540	-	90
21	Sep 30, 2016	-	-	144	-	1984	4134	-	180
22	Oct 31, 2016	-	-	368	-	1832	3920	-	120
23	Nov 30, 2016	-	-	352	-	1233	3390	-	150
24	Dec 31, 2016	-	-	302	-	1729	3524	-	180
25	Jan 31, 2017	0	562	184	60	2785	2308	0	60
26	Feb 28, 2017	0	250	44	66	2640	2884	0	120
27	Mar 31, 2017	0	200	45	23	1636	2972	0	0
28	Apr 30, 2017	0	690	88	45	446	2865	150	239
29	May 31, 2017	0	180	44	22	776	3502	270	155
30	Jun 30, 2017	0	218	100	23	1640	6722	345	539
31	Jul 31, 2017	0	0	45	0	506	1504	80	0
32	Aug 31, 2017	0	244	205	47	3552	4567	548	485
33	Sep 30, 2017	0	100	325	22	3916	5158	228	78
34	Oct 31, 2017	0	90	160	167	3508	4423	2190	75
35	Nov 30, 2017	0	0	243	1020	4183	3268	940	69
36	Dec 31, 2017	?	?	?	?	?	?	?	?
37	Jan 31, 2018	0	1240	195	20[illegible]	[illegible]56	2645	1430	71

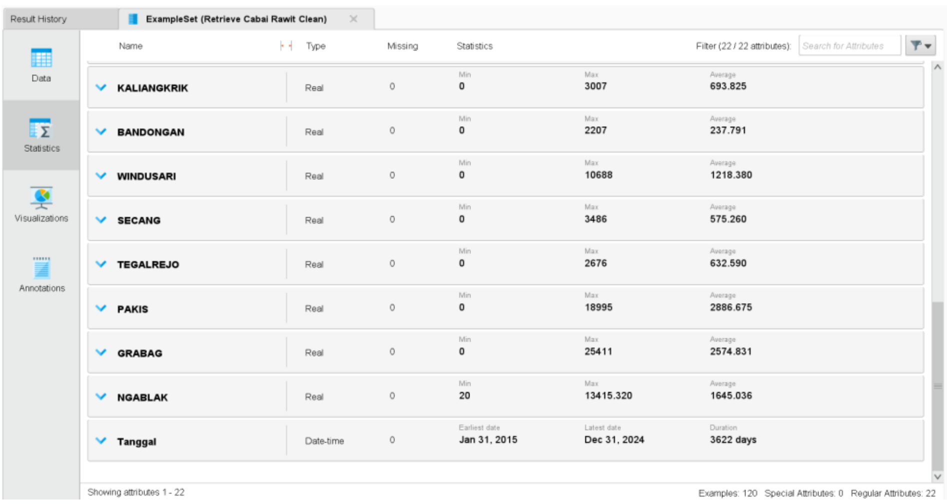
Figure 3. Identification of initial data discrepancies (continued)

Through this preprocessing stage, the data becomes cleaner and ready to be used in predictive modeling of chili production in Magelang Regency, as shown in the following figure.



Row No.	Tanggal	SALAMAN	BOROBUD...	NGLUWAR	SALAM	SRUMBUNG	DUKUN	MUNTILAN	MUNGKID	SAWANGAN	CANI
1	Jan 31, 2015	0	60	0	0	2387	2014	0	150	25	19
2	Feb 28, 2015	0	420	0	0	1582	1756	0	152	43	32
3	Mar 31, 2015	0	420	0	0	1352	1394	0	210	106	19
4	Apr 30, 2015	0	200	0	0	1494	1300	0	210	265	18
5	May 31, 2015	0	190	0	0	1408	1368	0	180	344	33
6	Jun 30, 2015	0	0	0	0	1678	1904	0	150	516	14
7	Jul 31, 2015	0	0	0	0	1516	2070	0	100	301	14
8	Aug 31, 2015	0	0	0	0	1478	2010	0	102	172	17
9	Sep 30, 2015	0	0	0	0	1411	2560	0	60	258	16
10	Oct 31, 2015	0	0	0	52	2004	3481	0	150	43	16
11	Nov 30, 2015	0	0	0	0	2316	3720	0	180	43	15
12	Dec 31, 2015	0	0	47	26	2567	3270	0	150	0	35
13	Jan 31, 2016	0	0	47	51	2449	2660	0	60	0	20
14	Feb 29, 2016	0	453	47	51	2137	2580	0	150	0	15
15	Mar 31, 2016	0	690	46	46	1458	2720	0	120	276	25
16	Apr 30, 2016	0	918	48	22	670	3040	0	210	88	25
17	May 31, 2016	0	1224	92	0	652	3068	0	180	368	16
18	Jun 30, 2016	0	1224	132	0	1222	3140	0	150	176	16

Figure 4. Clean Data after Preprocessing



Name	Type	Missing	Statistics		
KALIANGKRIK	Real	0	Min 0	Max 3007	Average 693.825
BANDONGAN	Real	0	Min 0	Max 2207	Average 237.791
WINDUSARI	Real	0	Min 0	Max 10688	Average 1218.380
SECANG	Real	0	Min 0	Max 3486	Average 575.260
TEGALREJO	Real	0	Min 0	Max 2676	Average 632.590
PAKIS	Real	0	Min 0	Max 18995	Average 2886.675
GRABAG	Real	0	Min 0	Max 25411	Average 2574.831
NGABLAK	Real	0	Min 20	Max 13415.320	Average 1645.036
Tanggal	Date-time	0	Earliest date Jan 31, 2015	Latest date Dec 31, 2024	Duration 3622 days

Figure 5. Data Statistics after Preprocessing

The data after preprocessing is the main dataset that is entered into the model through the Retrieve Data operator [46]. This dataset has 21 attributes, each representing the amount of chili production in each sub-district.

3.3. Training and modeling of neural network methods

The series in the data training process produces models or patterns according to the prediction modeling in AI Studio as follows:

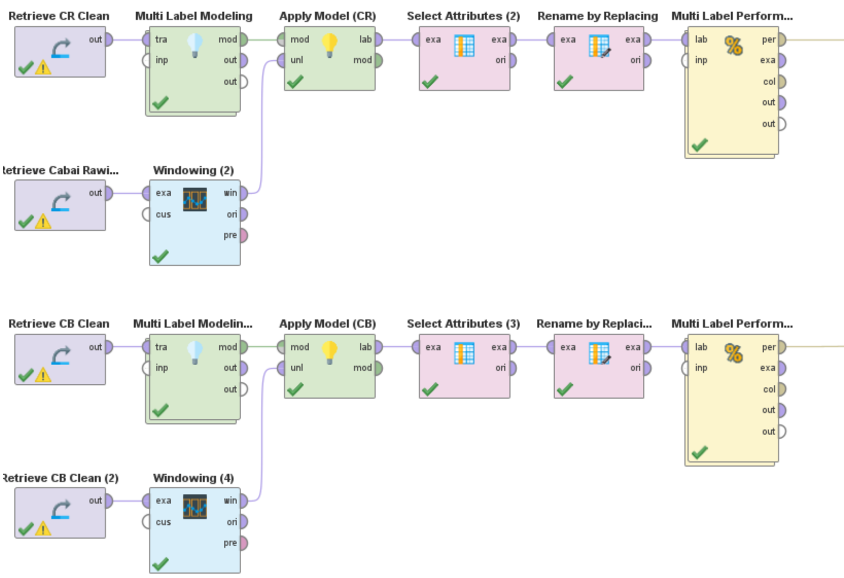


Figure 6. Predictive Modeling Flow in AI Studio [43]

This dataset has 21 attributes, each of which represents the amount of chili production in 21 sub-districts in Magelang Regency. Since the model must predict chili production for each sub-district, it is necessary to train the model with 21 different targets. To handle this, the multilabel modeling method [48] is used, which allows the model to learn and predict multiple targets in one training process, allowing the model to learn and predict more than one target at a time.

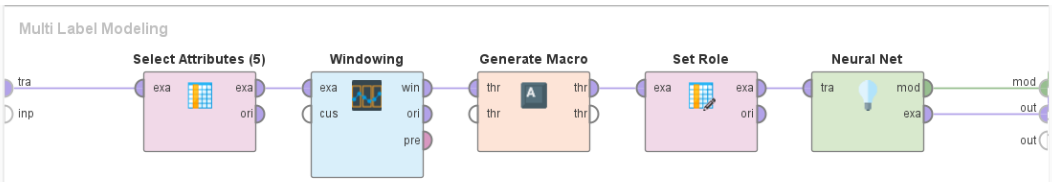


Figure 7. Model Training in Multi-Label Modeling [43]

Figure 9 shows the process of training a prediction model using the multi-label modeling function in Altair AI Studio. In this process, the Neural Network method is used with various parameter configurations to find the model with the best performance and optimal prediction accuracy. Model training begins with the Select Attribute operator, which is used to select one production attribute in the dataset to be processed at a time [23]. The selection of one attribute aims to save computing resources and speed up the training process. In addition, this approach is also chosen because there is no direct relationship between the amount of production in one sub-district and another. Therefore, model training is focused on one target label separately without being influenced by production data from other sub-districts.

The selected data, windowing process is applied to form a dataset suitable for time series prediction. In this study, a 13-month sliding window approach is used, with each training consisting of production data for the previous 12 months as input features, while 1 month is used as a prediction target. With this method, the model can capture the annual seasonal pattern of chili production and predict the next month's production based on historical trends in each sub-district.

The prediction dataset is still in the form of a window data set, the attribute selection process is carried out using the Select Attribute operator to filter only relevant attributes, namely date, actual production data, and prediction results in each sub-district. The Rename operator is also used to rename attributes to make them easier to understand. The result is a more structured dataset, consisting of 1 date attribute [48], 21 actual production attributes in each sub-district, and 21 predicted chili production results attributes in each sub-district.

3.4. Performance Testing and Evaluation

Performance evaluation is performed using the multi-label performance function, which allows evaluation to be performed automatically for each label because the prediction model has 21 target labels. The Performance Regression operator is used to assess the accuracy of the prediction model through several key metrics. Root Mean Squared Error (RMSE) serves to measure the average deviation between the predicted value and the actual value, by giving a higher weight to larger errors [3]. Therefore, the smaller the RMSE value, the better the prediction performance of the model. Meanwhile, Mean Absolute Error (MAE) calculates the average absolute difference between the actual value and the predicted value, thus providing a direct measure of the accuracy of the prediction model. In this study, RMSE and MAE were chosen as metrics to assess the overall accuracy level of the prediction results. In addition, the correlation coefficient (r) is used to evaluate the strength of the linear relationship between the actual and predicted values. A high correlation value (approaching 1) indicates that the model is able to capture trend patterns in the data well, while a low correlation value indicates that the model's prediction ability is inadequate. This correlation analysis is applied to determine the extent to which the model can capture trends and seasonal patterns in the dataset [26].

The figure below shows the output results of the dataset obtained from the developed model experiment. The result shows the prediction of chili production for each sub-district in Magelang Regency. Information on the prediction results can be seen in the "prediction" attribute, which displays the estimated chili production per sub-district using the Backpropagation Algorithm [27].


Open in Turbo Prep Auto Model Interactive Analysis Filter (107 / 107 examples): all

Row No.	Last Tangg...	prediction(SALAMA...	SALAMAN	prediction(BOROBUDUR...	BOROBUDUR ↓	prediction(NGLUWAR ...	NGLUWAR	prediction(SALAM -...
75	Mar 31, 2022 ...	210.340	210	7246.254	6860	430.645	438	141.838
74	Feb 28, 2022...	219.600	222	6509.367	6510	548.678	500	1264.416
106	Oct 31, 2024 ...	667.174	667	5766.411	5832.390	210.167	206.410	4861.663
86	Feb 28, 2023...	138.908	141	5599.800	5626	530.734	514	3005.634
76	Apr 30, 2022 ...	195.113	210	5519.963	5250	587.170	560	1361.197
87	Mar 31, 2023 ...	819.766	821	4645.722	4672	657.175	661	5941.964
88	Apr 30, 2023 ...	146.320	146	4716.359	4672	634.574	655	1883.603
54	Jun 30, 2020 ...	-3.131	0	4646.412	4492	101.041	20	251.103
89	May 31, 2023...	893.422	895	4425.086	4484	634.231	645	1398.150
83	Nov 30, 2022 ...	317.008	317	3912.542	3603	812.536	783	673.600
85	Jan 31, 2023 ...	19.051	24	3638.712	3350	728.003	732	2182.351
73	Jan 31, 2022 ...	123.635	140	3355.553	3250	189.984	143.500	1125.188
72	Dec 31, 2021...	148.589	135	3031.105	3082	127.058	182	2602.708
100	Apr 30, 2024 ...	197.685	198	3006.234	3063	694.951	688.600	2910.758
99	Mar 31, 2024 ...	148.533	149	3035.908	2940	603.867	608	2448.722
77	May 31, 2022...	635.024	635	3047.449	2870	721.155	700	1954.040
51	Mar 31, 2020 ...	-3.131	0	842.809	2742	38.766	28	173.991
98	Feb 29, 2024...	121.885	122	3011.080	2732	758.946	751.200	702.503

ExampleSet (107 examples,22 special attributes,21 regular attributes)

Figure 8. Prediction Model Output

To determine the optimal Neural Network architecture in predicting chili production, several model configurations were tested with both datasets. The model performance assessment is based on three main metrics, namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient [26]. In addition, an analysis of the standard deviation of each metric was also carried out to measure the extent of prediction consistency in various regions.

In the initial stage, the number of cycles in the model training process was set at 500 cycles as the initial value. The selection of this number aims to identify the model architecture that provides the best performance, before further tuning is carried out to determine the optimal number of training iterations. Although each architecture was trained for 500 training cycles, the computation time remains within manageable limits, considering the relatively small size of the dataset. Therefore, 500 training cycles are considered a reasonable choice in the initial stage of testing various model architectures [46].

From several experiments on the configuration of the prediction model architecture, the model with the best performance was obtained, as shown in Table 5 for the performance of the Large Chili production prediction model and Table 6 for the performance of the Bird's eye chili pepperproduction prediction model.

Table 5. Performance of Large Chili Production Prediction Model with several model architectures

Architecture	RMSE	MAE	Correlation
12 – 5 – 1	712.390 +/- 1089.775	478.793 +/- 750.158	0.863 +/- 0.085
12 – 10 – 1	696.018 +/- 1076.514	449.423 +/- 706.371	0.866 +/- 0.089
12 – 15 – 1	744.401 +/- 1178.456	541.118 +/- 910.541	0.871 +/- 0.073
12 – 20 – 1	729.713 +/- 1183.202	499.429 +/- 861.908	0.870 +/- 0.071
12 – 25 – 1	691.381 +/- 1052.801	442.387 +/- 672.019	0.866 +/- 0.090
12 – 30 – 1	752.578 +/- 1248.757	504.606 +/- 846.078	0.866 +/- 0.077

Table 6. Performance of Chili Pepper Production Prediction Model with several model architectures

Architecture	RMSE	MAE	Correlation
12 – 5 – 1	573.196 +/- 619.136	362.707 +/- 370.903	0.872 +/- 0.100
12 – 10 – 1	571.655 +/- 623.674	375.145 +/- 397.583	0.879 +/- 0.092
12 – 15 – 1	570.121 +/- 602.069	354.108 +/- 347.987	0.877 +/- 0.093
12 – 20 – 1	575.730 +/- 616.592	353.836 +/- 369.165	0.881 +/- 0.091
12 – 25 – 1	603.467 +/- 634.124	401.095 +/- 390.749	0.876 +/- 0.090
12 – 30 – 1	598.651 +/- 671.945	391.153 +/- 451.266	0.874 +/- 0.098

~~Data statistik dari hasil prediksi yang dihasilkan menggunakan Neural Network dengan~~ arsitektur terbaik berda

Statistical data from the prediction results generated using the Neural Network with the best architecture based on experiments on large chili in this study, namely 12 - 25 - 1, with the lowest RMSE value of 691.381 and the lowest MAE of 442.387, and a stable correlation of 0.866. In addition, this architecture has the lowest standard deviation of ±1052.801 for RMSE and ±672.019 for MAE, indicating that the prediction results are more consistent across sub-districts. Meanwhile, a more complex architecture, 12 - 30 - 1, does not improve accuracy and instead produces more uncertain prediction results, indicating that the model is less able to predict data well.

For the bird's eye chili pepper dataset, the best architecture is 12 – 15 – 1, with the lowest RMSE of 570.121, the lowest MAE of 354.108, and a high correlation of up to 0.877. In addition, this architecture also has the lowest standard deviation of ±602.069 for RMSE and ±347.987 for MAE, which means that the prediction results are more stable in all sub-districts. Although the 12 – 20 – 1 architecture produces the highest correlation of 0.881, its RMSE value is also higher at 575.730, so 12 – 15 – 1 provides the best balance between error rate and ability to capture patterns from data.

After selecting the best performing architecture, various numbers of training cycles were tested to see how they affect the model performance. To determine the optimal number of training cycles, the selected architecture was trained with 500 to 3500 cycles, with an increase of 500 cycles in each trial. The resulting model from these experiments showed the performance as presented in the following table.

Table 7. Performance of the large chili production prediction model with the 12-25-1 architecture

Training Cycles	RMSE	MAE	Correlation
500	691.381 +/- 1052.801	442.387 +/- 672.019	0.866 +/- 0.090
1000	514.253 +/- 776.690	360.769 +/- 569.624	0.926 +/- 0.060
1500	467.210 +/- 711.916	345.883 +/- 578.036	0.945 +/- 0.051
2000	406.815 +/- 600.032	300.452 +/- 494.166	0.954 +/- 0.048
2500	378.722 +/- 574.293	273.514 +/- 454.522	0.960 +/- 0.040
3000	353.592 +/- 523.842	252.915 +/- 407.839	0.965 +/- 0.036
3500	324.300 +/- 456.411	229.006 +/- 346.240	0.968 +/- 0.034

Table 8. Performance of the Chili Pepper Production Prediction Model with the 12-15-1 Architecture

Training Cycles	RMSE	MAE	Correlation
500	570.121 +/- 602.069	354.108 +/- 347.987	0.877 +/- 0.093
1000	469.055 +/- 567.829	282.842 +/- 306.651	0.924 +/- 0.062
1500	419.554 +/- 544.795	259.503 +/- 311.016	0.944 +/- 0.049
2000	392.600 +/- 521.389	250.121 +/- 313.312	0.954 +/- 0.042
2500	364.357 +/- 485.683	232.750 +/- 282.707	0.961 +/- 0.035
3000	342.878 +/- 461.384	218.383 +/- 262.895	0.965 +/- 0.033
3500	326.698 +/- 442.639	206.694 +/- 245.439	0.969 +/- 0.029

Statistical data from the prediction results, generated using the Neural Network with the best architecture based on the experiments in this study, namely 12 - 25 - 1 for the large chili prediction model and 12 - 15 - 1 for the bird's eye chili pepper prediction model. The results display the main statistical values of the prediction model, such as the minimum, maximum, and average values of the prediction results generated as seen in the figure below.

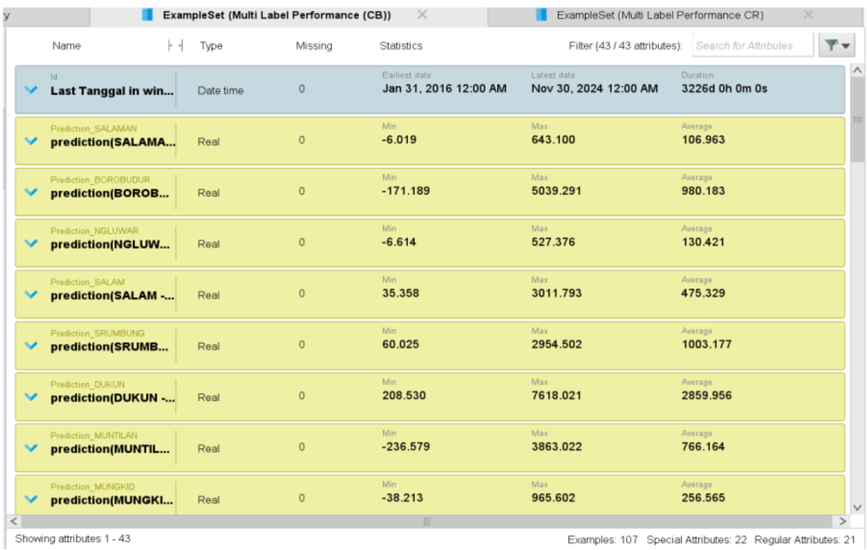


Figure 9. Statistics of prediction results for large chilies using the 12-25-1 model

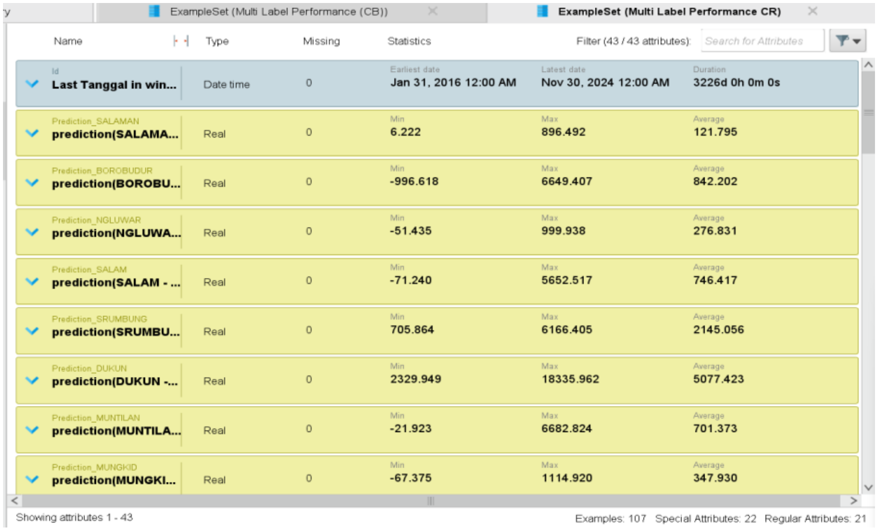


Figure 10. Statistics of prediction results of bird's eye chili pepperwith the 12-15-1 model

4. Conclusion

The Backpropagation algorithm on the Artificial Neural Network (ANN) developed to determine the prediction of large chili and bird's eye chili pepperproduction in this study produced the best model which had a Model Architecture configuration of 12 - 25 - 1 for predicting large chili production and Model Architecture 12 - 15 - 1 for predicting bird's eye chili pepper. The best results were obtained at 3500 training cycles, with the highest accuracy indicated by the RMSE value of 324,300, MAE 229,006, and correlation of 0.968 for the large chili model, and RMSE 326,698, MAE 206,694, and correlation of 0.969 for the bird's eye chili pepper model.

This Artificial Neural Network (ANN) based prediction model has high flexibility and can be developed to support various policies in the agricultural sector. With its adaptability, this system can be applied and further developed for various types of tasks and agricultural commodities.

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