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ANALYSIS OF WEATHER CHANGES FOR ESTIMATION OF SHALLOT CROPS FLUCTUATION USING HIDDEN MARKOV

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Abstract. *Climate change has an impact on increasing the temperature of the earth's surface or what is known as global warming. The impact of global warming will affect the pattern of precipitation, evaporation, water run-off, soil moisture and climate variations which are very volatile can threaten the success of horticultural production, especially shallots. Shallots are a strategic commodity but are strongly influenced by fluctuations in production. The development of shallots is one of them constrained by the weather/climate which affects the production of shallots. From these constraints, shallots are also a commodity that contribute significantly to inflation. Hidden Markov Models (HMM) is one of the stochastic processes when the future only depends on condition now, in markov chain all of the element observable, and the probability move to another probability. Prediction and estimation of shallot crops with rainfall input, temperature, and humidity is done with data starting in 2016 until 2020. Estimated shallot crops follows the optimum movement pattern of prediction shallot in each of each variable. The planting months that are usually carried out in the two districts are around February, May, June and September the lowest shallot crops in April or May because transition of rainy to dry season. And the highest shallot crops in October or November. The best accuracy of estimation is rainfall factor with MAPE 5,89% with high accuracy category while 5,84% in MAPE temperature and in 5,55% in humidity factor in category high.*

Keywords: *weather shallot crops, hidden markov.*

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1. INTRODUCTION

Climate change is a condition characterized by changes in world climate patterns that result in erratic weather phenomena. Climate change occurs due to changes in climate variables, such as air temperature and rainfall that occur continuously over a long period of more than 10 years [1]. Climate change has an impact on increasing the temperature of the earth's surface or what is known as global warming [2]. The impact of global warming (Global Warming) will affect the pattern of precipitation, evaporation, water run-off [3], [4]. Soil moisture and climate variations which are very volatile can threaten the success of horticultural production, especially shallots [5]. Shallots are a strategic commodity but are strongly influenced by fluctuations in production. The development of shallots is one of them constrained by the weather/climate which affects the production of shallots. From these constraints, shallots are also a commodity that contributes significantly to inflation [6].

Nganjuk Regency is the largest shallot production center in East Java and the second largest in Indonesia [7], [8], [9], [10]. In 2019, shallot production from Nganjuk Regency controlled 39.83 percent of all shallot production in East Java. So more than a third of East Java's shallot production is controlled by shallot production from Nganjuk. Shallot production in Nganjuk district in 2019: January reached 202,685 quintals, February decreased to 28,037 quintals, March increased to 29,840 quintals, April dropped dramatically to 7,315 quintals, May increased significantly by 127,170 quintals, June increased by 135,110 quintals, in July it fell to 67,170 quintals, in August it reached the highest value of 413,290 quintals, while in September it fell to 278,674 quintals, October fell to 112,453 quintals, November rose to 218,175 quintals and the lowest point of production in December was 4,580 quintals [9]. For development in order of improvement agricultural production of the East Java Agriculture Office implements conserving policies wetland agricultural land use area as agricultural land sustainable food crops to support food security, maintain the availability of employment in agriculture, maintain the balance of the environment, control the transfer of agricultural functions, securing production through controlling plant-disturbing organisms, controlling strategic infectious animal diseases and handling impacts natural disasters and climate change [4], [11]. In this study, the problem will be studied in the problem climate change is a matter of weather analysis as an estimate of production Shallot. From the background author got idea for using a Hidden Markov Model. HMMs can be used to estimate the unknown state of a process based on observed measurements [12], [13]. The model needs a probability for each state given the observations (emission probability) and state transition probability which encodes the probability of the process changing from one state to another [14], [15].

2. RESEARCH METHODS

2.1 Hidden Markov Model

Hidden Markov Models (HMM) is one of the stochastic process when the future only depend on condition now, in markov chain all of the element observable, and the probability move to another probability [16]. HMM have hidden state that non observable yet and this process markov chains are combined [12], [17], [18]. HMM represented as M=(A,B,π) is specified by the following probabilities [17]:

a. A vector of initial state probabilities, $\pi = \pi_i$
b. A matrix of transition probabilities, $A = a_{ij}$ where, $a_{ij} = P(S_i\,|S_j)$ and $P(S_i\,|S_j)$ is the conditional distribution of the present state, s_i given the previous state, s_j.
c. A matrix of emission/observation probabilities, $B = b_i\,(v_m)$ where, $b_i\,(v_m\,) = P(v_m\,|s_i)$ and $P(v_m\,|s_i)$ is the conditional distribution of v_m given the hidden state, s_i.

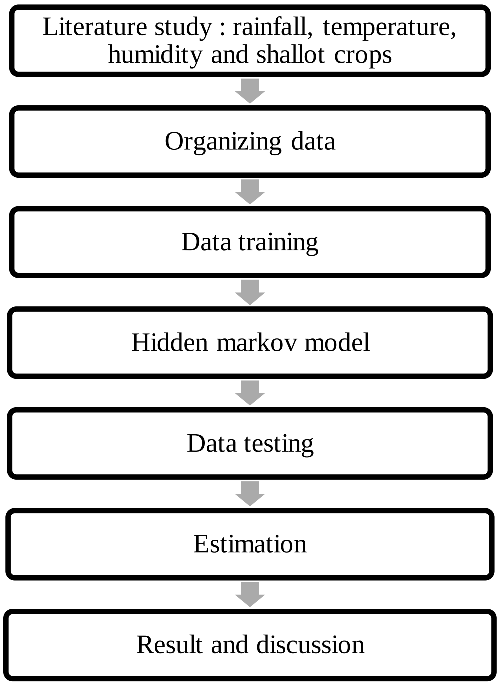

Figure 1. Research Methods Flowchart

2.2 Viterbi Algorithm

Author use the Viterbi algorithm to find the single best state sequence (path), based on dynamic programming, which takes such transition probabilities into account [17], [18].

Given state sequence $Q = S_1\, S_2 \ldots S_T$ and observable state $O = o_1\, o_2 \ldots o_T$, then define $\delta_t\,(i)$ as highest, path at time t that accounts for the first t observations and ends in $S(i)$ [19].

$$\delta_t\,(i) \equiv \max_{S_1\, S_2 \ldots S_{t-1}} p(S_1\, S_2 \ldots S_{t-1}, S_t = P_i, o_1\, o_2 \ldots o_T\,|\lambda) \qquad (1)$$

Then recursively calculate $\delta_{t+1}\,(i)$ and the optimal path can be read by backtracking from T , choosing the most probable at each instant [14], [17]. The algorithm is as follows:

a. Initialization

$$\delta_t(i) = \pi_i b_i\,(O_1) \qquad (2)$$

$$\Psi_1\,\,(i) = 0 \qquad (3)$$

b. Recursion

$$\delta_t\,\,(j) = \max_i \delta_{t-1}\,(i) a_{ij}.b_j\,(O_t) \qquad (4)$$

$$\Psi_1\,\,(j) = arg \max_i \delta_{t-1}\,(i) a_{ij} \qquad (5)$$

c. Termination

$$p^* = \max_i \delta_T(i) \qquad (6)$$

$$q_T^* = \underset{i}{arg\,max}\, \delta_T(i) \qquad (7)$$

d. Backtrack

$$q_t^* = \Psi_{t+1}(q_{t+1}^*), t = T-1, T-2, \ldots, 1 \qquad (8)$$

Generally, author divide state of variables become 6 states.

Observable state rainfall
O1 = rainfall decrease 350 – 201
O2 = rainfall decrease 200 – 101
O3 = rainfall decrease 100 – 0
O4 = rainfall increase 1 – 100
O5 = rainfall increase 101 – 200
O6 = rainfall increase 201 – 350

Observable state temperature
O1 = temperature decrease 1,6 – 1,1
O2 = temperature decrease 1,0 – 0,6
O3 = temperature decrease 0,5 – 0
O4 = temperature increase 0,1 – 0,5
O5 = temperature increase 0,6 – 1,0
O6 = temperature increase 1,1 – 1,6

Observable state humidity
O1 = humidity decrease 8, 55 – 5,1
O2 = humidity decrease 5 – 3,1
O2 = humidity decrease 3 – 0
O3 = humidity increase 0,1 – 4, 83
O4 = humidity increase 4,84 – 8, 45
O4 = humidity increase 8,46 – 12, 45

Hidden State
S1 = production decrease 200.000 – 425.000
S2 = production decrease 100.000 – 199.999
S3 = production decrease 0 – 99.999
S4 = production increase 0,1 – 99.999
S5 = production increase 100.000 – 199.999
S6 = production increase 200.000 – 425.000

$A = [a_{ij}]$ is matrix transition from observable such as rainfall, temperature, and humidity on table 1, table 2 and table 3

Table 1. Transition Probability Rainfall Observable State

Next State	O1	O2	O3	O4	O5	O6
O1	0.0	0.0	0.2	0.2	0.3	0.3
O2	0.08	0.12	0.2	0.4	0.1	0.1
O3	0.2	0.1	0.2	0.3	0.0	0.2
O4	0.1	0.2	0.1	0.1	0.2	0.3
O5	0.167	0.0	0.33	0.33	0.0	0.167
O6	0.1	0.1	0.3	0.1	0.2	0.2

Table 2. Transition Probability Temperatur Observable State

Next State	O1	O2	O3	O4	O5	O6
O1	0.1	0.1	0.1	0.2	0.3	0.2
O2	0.2	0.2	0.0	0.4	0.1	0.1
O3	0.1	0.1	0.2	0.3	0.1	0.2
O4	0.1	0.2	0.1	0.1	0.2	0.3
O5	0.1	0.0	0.3	0.3	0.2	0.1
O6	0.1	0.1	0.3	0.1	0.2	0.2

Table 3. Transition Probability Temperatur Observable State

Next state	O1	O2	O3	O4	O5	O6
O1	0.0	0.0	0.2	0.2	0.3	0.3
O2	0.1	0.2	0.2	0.3	0.1	0.1
O3	0.1	0.1	0.2	0.3	0.1	0.2
O4	0.1	0.2	0.1	0.1	0.2	0.3
O5	0.2	0.0	0.3	0.3	0.0	0.2
O6	0.1	0.1	0.3	0.1	0.2	0.2

$B = [b_{jm}]$ is emission matrix that show probability between rainfall and crop production, temperature and crop production, humidity and crop production represented on Table 4, Table 5 and Table 6.

Table 4. Probability between Rainfall and Corps Production

Next State	S1	S2	S3	S4	S5	S6
O1	0.1	0.2	0.1	0.1	0.2	0.3
O2	0.2	0.0	0.3	0.3	0.0	0.2
O3	0.1	0.1	0.3	0.1	0.2	0.2
O4	0.1	0.1	0.2	0.3	0.1	0.3
O5	0.1	0.2	0.1	0.1	0.2	0.167
O6	0.2	0.0	0.3	0.3	0.0	0.2

Table 5. Probability between Temperatur and Corps Production

Next State	S1	S2	S3	S4	S5	S6
O1	0.1	0.2	0.2	0.3	0.1	0.3
O2	0.1	0.1	0.2	0.3	0.1	0.2
O3	0.1	0.2	0.1	0.1	0.2	0.2
O4	0.1	0.1	0.2	0.3	0.1	0.3
O5	0.1	0.2	0.1	0.1	0.2	0.167
O6	0.2	0.0	0.3	0.3	0.0	0.2

Table 6. Probability between Humidity and Corps Production

Next State	S1	S2	S3	S4	S5	S6
O1	0.1	0.2	0.2	0.3	0.1	0.3
O2	0.1	0.2	0.1	0.1	0.2	0.2
O3	0.2	0.0	0.3	0.3	0.0	0.2
O4	0.1	0.1	0.3	0.1	0.2	0.3
O5	0.1	0.2	0.1	0.1	0.2	0.167
O6	0.2	0.0	0.3	0.3	0.0	0.2

Number of state $S_1 = 8, S_2 = 8, S_3 = 2, S_4 = 2\ S_5 = 3$ and $S_6 = 5$, and π is the distribution of initial state then π =[0,34 0,34 0,08 0,21] And then the initial input of A, B, and π decode and calculate to viterbi algorithm [12], [17].

Data processed in the Hidden Markov Model is data on the year 2016-2020 by creating new parameters Hidden Markov Model [6], [20], [24]. if given a certain sequence of sequences can find the most likely state transition set along with the probability of the result, then from the predicted result of the year data 2016 displays into data testing used for estimation rice production in the following year [7], [8], [9], [10], [25]. While training data analyzed the pattern of movement and how big the accuracy of the viterbi algorithm that have been prepared. The expectation-maximisation (EM) [18] is one of the commonly used algorithms to solve HMM problems, which is an iterative algorithm based on using the maximum likelihood to estimate the parameters of the statistical model with hidden variables [15]. The value of the increase or decrease later used for estimation is determined by calculating the average increase/ decrease in each state:

S_1 with an average decrease of 237868 quintals
S_2 with an average decrease of 100079 quintals
S_3 with an average increase of 33632 quintals
S_4 with an average increase of 12155 quintals
S_5 with an average increase of 73381 quintals
S_6 with an average increase of 271157 quintals

3. RESULTS AND DISCUSSION

a. Training Data

The result of Training rainfall, humidity and temperature data and crop production 2016-2020, then result of prediction based from state sequence:

Table 7. Result of training between Humidity and Corps Production

Year	Month	Real	Temp	Humidity	Rain
2016	1	148850	151690	152190	153390
	2	93395	97110	95210	92310
	3	62107	62530	63330	66530
	4	7005	7150	7320	7043
	5	46437	45790	45390	44490
	6	57320	53630	56632	54651
	7	93963	96470	94470	97870
	8	380512	376544	356522	344567
	9	29742	28385	28385	27264
	10	331624	383924	375624	393930
	11	55679	66123	67523	68343
	12	18044	17665	16653	16590
2017	1	84912	72070	87070	82070
	2	10456	10491	10910	9234
	3	33109	30330	32987	35435
	4	9921	9317	9256	10342
	5	60216	58590	55987	58123
	6	125305	118430	114390	113900
	7	55078	51504	54327	51504
	8	432927	444344	469690	454344
	9	64753	69764	70453	68764
	10	201194	207070	203456	200765
	11	159760	167144	157133	160782
	12	32405	34450	32445	33564
2018	1	139969	139870	140650	140545
	2	43801	42710	41352	43212
	3	9425	9130	9564	9345
	4	22219	20970	20070	21090
	5	49885	49810	48103	50234
	6	101902	99230	111029	100876
	7	92155	93045	91304	92387
	8	516935	509378	496378	518745
2018	9	247650	266684	267546	246545
	10	89383	86323	88788	88667
	11	210760	197656	194109	196788
	12	67	657	768	887
2019	1	202685	191090	200678	210984

Year	Month	Real	Temp	Humidity	Rain
	2	28037	25164	31564	28656
	3	29840	22470	25348	26546
	4	7315	7890	7540	7565
	5	127170	128010	127674	128532
	6	135110	136150	137473	137319
	7	67170	66224	67491	68032
	8	413290	435302	376845	429281
	9	278678	273604	281814	278304
	10	112543	113853	113484	114093
	11	218175	222322	241858	216994
	12	4580	4170	4282	4224
2020	1	160370	172010	154340	165980
	2	41937	43430	45730	47430
	3	35320	30270	31150	30344
	4	10167	15690	13990	15577
	5	100496	98530	106830	104530
	6	130230	133950	128909	139869
	7	62325	64024	62874	64884
	8	420423	389444	447744	419444
	9	266778	269518	257899	269518
	10	291222	296824	255124	298679
	11	201175	229664	227964	229664
	12	10165	9970	9520	10070

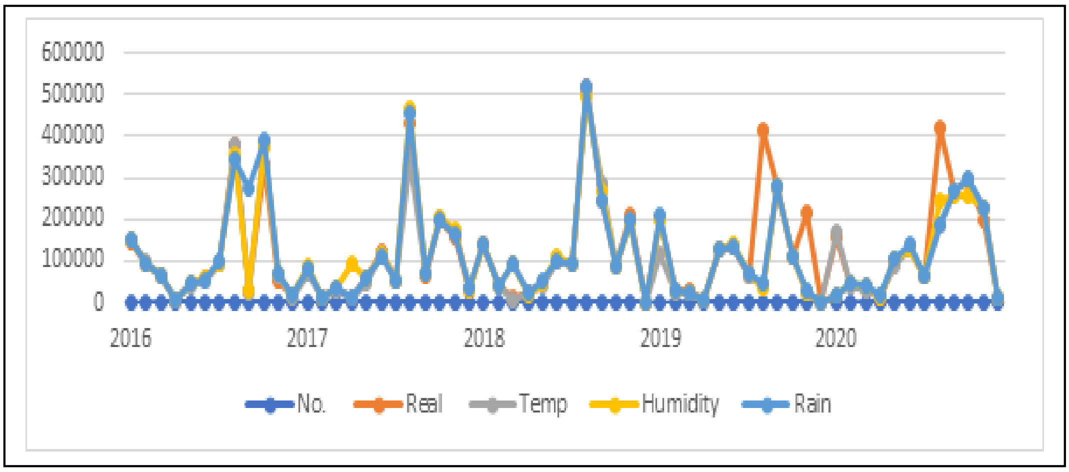

Figure 2. Research Methods Flowchart

b. Testing Data

Based on the results of testing estimation of rice production with rainfall, temperature and humidity factors, in table 10 then the estimation of Shallot production in year 2020 based from means of rainfall, temp and humidity factor month 1 produce 166505 quintals, and decrease in month 2 become 121925 quintals and decrease again in month 3 become 77345 and then become lowest in month 4 become 32765. After month 5 increase to 65605 quintal, and month 6 increase become 98445, month 7 131285, month 8 351449 quintals. And in month 9 decrease again become 128755, but increase again in month 10 become 361359. To 2 last month of 2021 become 146045 and decrease again become 101465 quintals. The estimation of Shallot production in year 2022 based from temp factor month 1 produce 56885 quintals, and decrease in month 2 become 89725 quintals and decrease again in month 3 become 45145 and then become lower in month 4 become 77985. After month 5 decrease to lowest become 33405 quintal, and month 6 increase become 66245, month 7 164830, month 8 146057 quintals. And in month 9 increase again become 284579, but decrease again in month 10 become 61885. To 2 last month of 2021 become 291959 and decrease again become 69265 quintals.

Table 8. Estimation Data of Shallot Crop in Nganjuk in 2021 and 2022

Year	Month	Estimation Factors		
		Temp	**Humidity**	**Rain**
2021	1	156595	181690	161230
	2	112015	137110	116650
	3	67435	92530	72070
	4	22855	47950	27490
	5	55695	80790	60330
	6	88535	113630	93170
	7	121375	146470	126010
	8	351449	376544	356084
	9	128755	153850	133390
	10	358829	383924	363464
	11	136135	161230	140770
	12	91555	116650	96190
2022	1	46975	72070	51610
	2	79815	104910	84450
	3	35235	60330	39870
	4	68075	93170	72710
	5	23495	48590	28130
	6	56335	81430	60970
	7	89175	114270	291044
	8	44595	69690	323884
	9	274669	299764	279304
	10	51975	77070	56610
	11	282049	307144	286684
	12	59355	84450	63990

c. Accuration

Positioning best performance estimates are available rainfall factor with MAPE 5,89% with high accuracy category whereas in MAPE temperature and humidity factor 5, 84% and 5,55% entered in the high accuracy category. But accuracy is still good in the year second and fourth, in the eighth year accuracy is still reasonable category although the category is close to low accuracy [12].

4. CONCLUSIONS

Based on the results of the analysis and discussion presented in the previous chapter, the following conclusions can be drawn:

1. Hidden Markov model can be used to predict onion production data with prediction division is done up to 6 states.
2. Prediction and estimation of shallot crops with rainfall input, temperature, and humidity is done with data starting in 2016 until 2020, Estimated shallot crops follows the optimum movement pattern of prediction shallot in each variables.
3. Based on the results of testing by Hidden Markov Model estimation of rice production with rainfall, temperature and humidity the estimation of Shallot production from January become decrease until the lowest production in May. And then increase again in June, July and August. In September decrease again but increase become highest level in October. In November decrease again until December.
4. The planting months that are usually carried out in the two districts are around February, May, June, and September. The lowest shallot crops in April or May because transition of rainy to dry season. And the highest shallot crops in October or November. The best accuracy of estimation is rainfall factor with MAPE 5,89% with high accuracy category while 5,84% in MAPE temperature and in 5,55% in humidity factor in high category.

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REFERENCES

[1] NationalGeographic,“https://www.nationalgeographic.org/encyclopedia/climate-change/.” https://www.nationalgeographic.org/encyclopedia/climate-change/.
[2] NASA, “The Effect of Climate Change.” https://climate.nasa.gov/effects/.
[3] M. Chen *et al.*, “A reinforcement learning approach to irrigation decision-making for rice using weather forecasts,” *Agric. Water Manag.*, vol. 250, no. May 2020, p. 106838, 2021, doi: 10.1016/j.agwat.2021.106838.
[4] Y. T. Tseng, S. Kawashima, S. Kobayashi, S. Takeuchi, and K. Nakamura, “Forecasting the seasonal pollen index by using a hidden Markov model combining meteorological and biological factors,” *Sci. Total Environ.*, vol. 698, p. 134246, 2020, doi: 10.1016/j.scitotenv.2019.134246.
[5] O. Stoner and T. Economou, “An advanced hidden Markov model for hourly rainfall time series,” *Comput. Stat. Data Anal.*, vol. 152, p. 107045, 2020, doi: 10.1016/j.csda.2020.107045.
[6] Badan Pusat Statistik Provinsi Jawa Timur, *Provinsi Jawa Timur dalam Angka Tahun 2016.* Surabaya: Badan Pusat Statistik Provinsi Jawa Timur. Surabaya., 2016.
[7] Badan Pusat Statistik Provinsi Jawa Timur, *Analisis Data Bawang Merah dan Cabai Provinsi Jawa Timur 2017*. Surabaya: Badan Pusat Statistik Provinsi Jawa Timur., 2017.
[8] Badan Pusat Statistik Provinsi Jawa Timur., *Analisis Data Bawang Merah dan Cabai Provinsi Jawa Timur 2018.* Surabaya: Badan Pusat Statistik Provinsi Jawa Timur., 2018.
[9] Badan Pusat Statistik Provinsi Jawa Timur., *Analisis Data Bawang Merah dan Cabai Provinsi Jawa Timur 2019.* Surabaya: Badan Pusat Statistik Provinsi Jawa Timur., 2019.
[10] Badan Pusat Statistik Provinsi Jawa Timur., *Statistik Hortikultura Provinsi Jawa Timur 2020*. Surabaya: Badan Pusat Statistik Provinsi Jawa Timur., 2020.
[11] S. Andriyas and M. McKee, “Exploring irrigation behavior at Delta, Utah using hidden Markov models,” *Agric. Water Manag.*, vol. 143, pp. 48–58, 2014, doi: 10.1016/j.agwat.2014.06.010.
[12] Kulkarni, *Introduction to Modeling and Analysis of Stochastic Systems*, vol. 102. 2011.
[13] J. Luo, T. Klein, Q. Ji, and C. Hou, “Forecasting realized volatility of agricultural commodity futures with infinite Hidden Markov HAR models,” *Int. J. Forecast.*, no. xxxx, 2019, doi: 10.1016/j.ijforecast.2019.08.007.
[14] M. Pastell and L. Frondelius, “A hidden Markov model to estimate the time dairy cows spend in feeder based on indoor positioning data,” *Comput. Electron. Agric.*, vol. 152, no. June, pp. 182–185, 2018, doi: 10.1016/j.compag.2018.07.005.
[15] M. Soleimani, F. Campean, and D. Neagu, “Integration of Hidden Markov Modelling and Bayesian Network for fault detection and prediction of complex engineered systems,” *Reliab. Eng. Syst. Saf.*, vol. 215, no. May, p. 107808, 2021, doi: 10.1016/j.ress.2021.107808.
[16] P. Zucchini, W., Guttorp, “A Hidden Markov Model for Space-Time Precipitation,” vol. 27, no. 8, pp. 1917–1923, 1991.
[17] J. W. Hansen, A. Mishra, K. P. C. Rao, M. Indeje, and R. K. Ngugi, “Potential value of GCM-based seasonal rainfall forecasts

for maize management in semi-arid Kenya," *Agric. Syst.*, vol. 101, no. 1–2, pp. 80–90, 2009, doi: 10.1016/j.agsy.2009.03.005.
[18] M. J. Puma and B. I. Cook, "Effects of irrigation on global climate during the 20th century," *J. Geophys. Res. Atmos.*, vol. 115, no. 16, pp. 1–15, 2010, doi: 10.1029/2010JD014122.
[19] lawrence R. Rabiner., "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," *Neurocomputing*, vol. 12, no. 4. pp. 371–373, 1996, doi: 10.1016/0925-2312(96)00016-1.
[20] Badan Pusat Statistik Provinsi Jawa, *Provinsi Jawa Timur dalam Angka Tahun 2017*. Surabaya, 2017.
[21] Badan Pusat Statistik Provinsi Jawa Timur, *Provinsi Jawa Timur dalam Angka Tahun 2018*. Surabaya, 2018.
[22] Badan Pusat Statistik Provinsi Jawa Timur, *Provinsi Jawa Timur dalam Angka Tahun 2019*. Surabaya: Badan Pusat Statistik Provinsi Jawa Timur, 2019.
[23] Badan Pusat Statistik Provinsi Jawa Timur, *Provinsi Jawa Timur dalam Angka Tahun 2020*. Surabaya: Badan Pusat Statistik Provinsi Jawa Timur, 2020.
[24] A. Stanislavsky, W. Nitka, M. Małek, K. Burnecki, and J. Janczura, "Prediction performance of Hidden Markov modelling for solar flares," *J. Atmos. Solar-Terrestrial Phys.*, vol. 208, no. July, p. 105407, 2020, doi: 10.1016/j.jastp.2020.105407.
[25] Badan Pusat Statistik Provinsi Jawa Timur, *Analisis Data Bawang Merah dan Cabai Provinsi Jawa Timur 2016*. Surabaya: Badan Pusat Statistik Provinsi Jawa Timur, 2016.