

Optimization of Backpropagation Method with PSO to Improve Prediction of Land Area and Rice Productivity

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Abstract: This research aims to optimize the Backpropagation method using Particle Swarm Optimization (PSO) to improve the accuracy of prediction of harvest area and rice productivity. The results show that the best architecture for prediction of harvest area is 3-15-1, with a Mean Squared Error (MSE) value of 0.0049980 for standard Backpropagation, and 0.00092376 after being optimized with PSO. Meanwhile, for rice productivity prediction, the best architecture is also 3-15-1, with an MSE value of 0.0049998 for standard Backpropagation, and 0.000435762 after using PSO. PSO optimization significantly reduces the MSE value, which indicates that this method is more accurate than standard Backpropagation. Predictions from 2024 to 2026 show more consistent results with some provinces experiencing an increase or decrease in harvested area and rice productivity that is different from the standard Backpropagation method. Based on the prediction accuracy that reaches 100% and the lower MSE value, it can be concluded that Backpropagation with PSO optimization is a superior method. The results of this study are useful for government, farmers, researchers, and policy makers in more effective agricultural planning and better risk management.

Keywords: Backpropagation, Particle Swarm Optimization, Harvest Area, Rice Productivity, Prediction

INTRODUCTION

Indonesia is an agricultural country with one of the largest farms in the world (Liundi et al., 2019). Rice is a food crop that plays an important role because it produces rice which is the staple food of the Indonesian people (Supriyatna et al., 2020). Until now, the government and farmers are trying to maintain the stability of food needs from rice yields. The government makes additional efforts to meet food needs by importing rice from other countries. This is due to the rampant diversion of paddy fields into airports, industries, housing, and so on (Kurniawati et al., 2023). The diversion of paddy fields affects the area of land and the productivity of rice produced. Plus the influence of extreme climate change adds to the lack of food security in Indonesia (Nubun & Yuliawati, 2022).

Extreme fluctuations in climate (Dhamira & Irham, 2020), changes in land use, and ineffective agricultural management techniques are the main factors that contribute to uncertainty in rice production. The impact of these fluctuations is not only limited to food security, but also directly affects farmers' welfare and national economic stability (Prabayanti et al., 2022). One of the main challenges in rice farming is unstable price fluctuations. Uncertainty in rice production and productivity has a direct impact on the price of rice in the market, which in turn affects people's purchasing power and national food availability. This calls for accurate and reliable predictions of rice land area and productivity to help manage risks and maintain rice price stability. Although there are various prediction methods that have been developed, one of which is the Backpropagation method (Saffaran et al., 2020), a technique in machine learning that is often used for prediction, has shortcomings in achieving optimal convergence points and high prediction accuracy.

Previous research related to this study is research on predicting rice production using Backpropagation Artificial Neural Networks. The data used in the research is time series data obtained from the Central Bureau of Statistics using data from 2011 to 2015 with 7 parameters. Tests were conducted using different learning rates, namely 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1 with the number of hidden layers 3, hidden neurons 7, and a maximum epoch of 10000. The result of this research is the minimum RMSE result which is 8.6918 with the parameter value of learning rate = 0.8, hidden layer = 3, hidden neuron = 4 with the number of epochs 10000 on 135 training data and 13 test data. Based on the test results of 5 fold cross validation on the stability of the test data, the average RMSE value is 8.2126. The study also explained that in order to add other parameters that affect the results of rice

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productivity, modifications can be made by adding other methods to the prediction of rice productivity, so that the learning process does not require large epochs and adding stopping conditions other than epochs to achieve convergence (Ramadhona et al., 2018).

The next research is rice harvest prediction research based on Artificial Neural Networks. The data used in the study is rice harvest data from 2014 to 2016 to predict future rice yields. Where the results of the study obtained an MSE value of 0.003487 with a maximum epoch of 1000. Backpropagation artificial neural networks can be used to build a prediction system for rice harvest season results (Anindyahadi et al., 2020).

Therefore, optimizing the Backpropagation method with optimization techniques such as Particle Swarm Optimization (PSO) (Irnanda et al., 2022) promises a significant improvement in the accuracy of predicting land area and rice productivity. In this context, research on optimizing the Backpropagation method with PSO (Bai et al., 2021) to improve the prediction of land area and rice productivity is very relevant and urgent. With the development of a more effective method, it is expected to make a significant contribution in maintaining the economic stability of farmers, national food security, and the stability of paddy prices in the domestic market.

The main objective of this research is to optimize the Backpropagation method using the Particle Swarm Optimization (PSO) technique (Purwinarko & Amalia Langgundi, 2023) to improve the prediction of land area and rice productivity. By combining these two methods, it is expected to improve prediction capabilities and minimize errors in estimating future land area and rice productivity. The urgency in this research is that optimizing the prediction of land area and rice productivity is important in the context of maintaining the sustainability of rice farming, which is the main food source for the community. Fluctuations in land area and rice productivity can affect food availability and farmers' economic stability. Therefore, the development of more accurate and efficient prediction methods is an urgent need.

LITERATURE REVIEW

Backpropagation is a learning algorithm in Artificial Neural Networks. Backpropagation was introduced in 1986 by Rumelhart, Hinton and William, then developed by Rumelhart and MC Cleland in 1988 (Bai et al., 2021). This algorithm is a Supervised Learning technique, which minimizes errors in the output produced in the form of a network. This algorithm consists of an Input section, Hidden Layer and Output (Agustyan et al., 2022). In general, Backpropagation is a type of Artificial Neural Network used for prediction, where the network is given a pair of patterns consisting of input patterns and desired patterns (Anindyahadi et al., 2020). The output of the last layer of the Hidden Layer is directly used as output in the Artificial Neural Network (Irnanda et al., 2022).

Particle Swarm Optimization is a pollution-based stochastic optimization algorithm developed by Eberhart and Kennedy in 1995. This algorithm is used as an optimization process with a random population and searches for the optimal solution by updating the generation (Saffaran et al., 2020). Particle Swarm Optimization (PSO) is based on the behavior of a flock of birds or fish that mimics the social behavior of these organisms (Salman et al., 2018). Swarm Intelligence System performs innovative intelligence deployment in solving optimization problems by taking inspiration from biological examples, such as the phenomenon of groups (Swarm) in animals where each group has individual behavior in performing joint actions to achieve the same goal.

$$v_i^t = wv_i^{t-1} + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t) \quad (1)$$

$$x_i^{t+1} = x_i^t + v_i^t \quad (2)$$

METHOD

In this study, we used a dataset obtained from the Central Bureau of Statistics website at the link <https://www.bps.go.id/id> with data on Rice Harvest Area and Productivity. We used data from 2018 to 2023 to predict 2024 to 2026. This research uses the Backpropagation method with Particle Smarm Optimization (PSO) optimization. Table one shows the sample data used in this research :

Table 1. Research Dataset

Province	Harvest Area (ha)				Productivity (ku/ha)			
	2018	2019	...	2023	2018	2019	...	2023
Aceh	329515,78	310012,46	...	254287,38	56,49	55,3	...	55,22
Sumatera Utara	408176,45	413141,24	...	406109,49	51,65	50,32	...	51,4
Sumatera Barat	313050,82	311671,23	...	300564,77	47,37	47,58	...	49,32
Riau	71448,08	63142,04	...	51914,14	37,28	36,56	...	39,68
Jambi	86202,68	69536,06	...	61236,64	44,44	44,57	...	45,06
Sumatera Selatan	581574,61	539316,52	...	504143,03	51,48	48,27	...	56,19
Bengkulu	65891,16	64406,86	...	57877,18	43,83	46,03	...	49,53
Lampung	511940,93	464103,42	...	530108,09	48,61	46,63	...	52,03
Kep. Bangka Belitung	17233,59	17087,81	...	15284,56	26,53	28,56	...	43,49
Kep. Riau	375,87	356,27	...	115,27	29,19	32,3	...	28,11
Dki Jakarta	673,37	622,59	...	542,93	72,76	53,96	...	49,26

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Province	Harvest Area (ha)				Productivity (ku/ha)			
	2018	2019	...	2023	2018	2019	...	2023
Jawa Barat	1707253,81	1578835,7	...	1583656,28	56,51	57,54	...	57,71
Jawa Tengah	1821983,17	1678479,21	...	1642761,23	57,63	57,53	...	55,3
Di Yogyakarta	93956,45	111477,36	...	105693,66	54,81	47,86	...	50,53
Jawa Timur	1751191,67	1702426,36	...	1698083,31	58,26	56,28	...	57,19
Banten	344836,06	303731,8	...	311199,73	48,94	48,41	...	54,19
Bali	110978,37	95319,34	...	108514,06	60,11	60,78	...	62,07
Nusa Tenggara Barat	289242,59	281666,04	...	287512,14	50,49	49,78	...	53,51
...	...	...	...	...	...	...	...	...
Papua Barat	7767,01	7192,15	...	5586,10	32,15	41,63	...	43,21
Papua	52411,95	54131,72	...	47756,38	42,57	43,48	...	43,4

The tools we use in this research is Matlab 2017a Tools to perform the training on training data and perform the evaluation on testing data using the Backpropagation Method and Particle Swarm Optimization (PSO) optimization. The stages in this research can be seen in Figure 1:

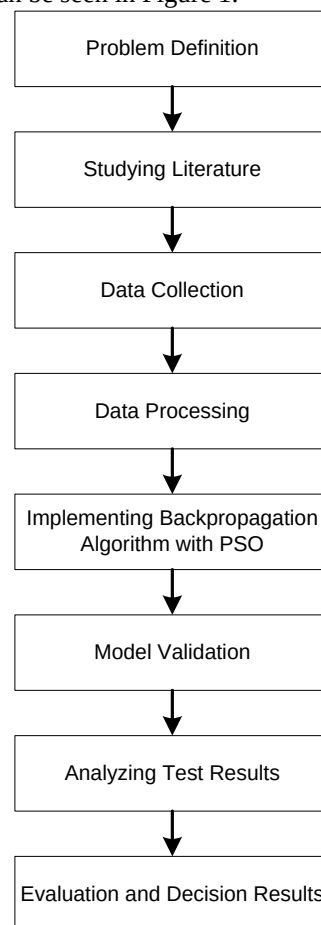


Figure 1. Research Stages

Based on Figure 1, explaining the stages of the research conducted, this stage begins to describe the problem of research with the harvest area and rice productivity in Indonesia. Then the stage of analyzing the problems of the harvest area and rice productivity, then studying related literature. The data collection stage is the stage where data is collected, then data processing is carried out before testing. Then the implementation stage of the Backpropagation Algorithm with PSO, then produce validation of the results of Backpropagation and Backpropagation with PSO. Furthermore, the stages of analyzing the test results and finally evaluating the prediction results for decision making.

Backpropagation is a learning algorithm in Artificial Neural Networks. Backpropagation was introduced in 1986 by Rumelhart, Hinton and William, then developed by Rumelhart and MC Cleland in 1988 (Bai et al., 2021). This algorithm is a Supervised Learning technique, which minimizes errors in the output produced in the form of a network. This algorithm consists of an Input section, Hidden Layer and Output (Agustyan et al., 2022). In general, Backpropagation is a type of Artificial Neural Network used for prediction, where the network is given a

pair of patterns consisting of input patterns and desired patterns (Anindyahadi et al., 2020). The output of the last layer of the Hidden Layer is directly used as output in the Artificial Neural Network (Irnanda et al., 2022).

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$$v_i^t = wv_i^{t-1} + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t) \quad (1)$$

$$x_i^{t+1} = x_i^t + v_i^t \quad (2)$$

RESULT

The steps to get the results of this research using Backpropagation with PSO Optimization can be explained as follows:

1. Training Process, where this stage is carried out training the data that has been prepared, namely by using data on the Harvest Area and Rice Productivity from 2018 to 2023.
2. Testing Process, where this stage is carried out by testing the data that has been prepared, the Testing Data used is data on the Harvest Area and Rice Productivity in 2020 to 2023.
3. Evaluation, where this stage will display a comparison of MSE and Prediction from Backpropagation and Backpropagation with PSO from 2024 to 2026.

This research uses data from 34 provinces in Indonesia. The architecture patterns used are 3-5-1, 3-10-1, 3-15-1, 3-20-1 and 3-25-1. The following is an example of the training process with the 3-10-1 architecture pattern used can be seen in Figure 2:

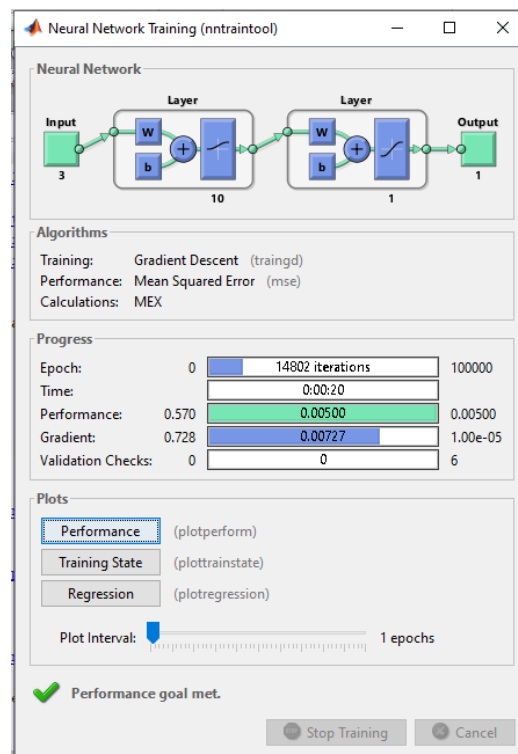


Figure 2. Example of Training Architecture 3-10-1

This research compares testing and prediction to provide accurate and effective results. The following is a recapitulation of the processing with data on Rice Harvest Area and Productivity which can be seen in Table 2 and Table 4.

Table 2. Testing Results of Harvested Area Data

No	Architecture	Testing		Backpropagation	Backpropagation + PSO
		Epoch	Time	MSE	MSE
1	3-5-1	4937	00.07	0,0049991	0,00460011
2	3-10-1	14439	00.19	0,0049996	0,00493172
3	3-15-1	2005	00.03	0,0049980	0,00092376
4	3-20-1	1882	00.03	0,0049973	0,00468606

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5	3-25-1	1148	00.02	0,0049991	0,00487051
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Table 3. Testing Results of Rice Productivity Data

No	Architecture	Testing		Backpropagation	Backpropagation + PSO
		Epoch	Time	MSE	MSE
1	3-5-1	6344	00.09	0,0049988	0,00482641
2	3-10-1	12756	00.17	0,0049997	0,00528507
3	3-15-1	8223	00.13	0,0049998	0,00435763
4	3-20-1	12737	00.17	0,0049995	0,00543261
5	3-25-1	5985	00.08	0,0049998	0,00513371

Based on Table 2 and Table 3, the best architecture is 3-15-1 architecture for Harvested Area and Rice Productivity. For Area of Harvest, the lowest MSE value is obtained in Backpropagation and PSO optimization with a value of 0.00092376 and an accuracy of 100%, with a time of 3 seconds and 2005 epochs. For Rice Productivity, the lowest MSE value is obtained in Backpropagation and PSO optimization with a value of 0.00435763 and an accuracy of 100%, with a time of 13 seconds and 8223 epochs. By using the 3-15-1 architecture pattern, the next step is to predict the Harvest Area and Rice Productivity both using Backpropagation and Backpropagation with PSO optimization. The following are the results of prediction recapitulation using Matlab 2017a tools. The following prediction recapitulation results can be seen in Table 4 and Table 5:

Table 4. Prediction Results of Harvested Area Data

Province	Backpropagation			Backpropagation and PSO		
	2024	2025	2026	2024	2025	2026
Aceh	257115,10	333425,32	259904,38	315225,13	295420,11	303627,06
Sumatera Utara	481003,17	773324,69	767384,58	414779,67	412275,21	430125,68
Sumatera Barat	169182,56	268117,52	447105,36	301629,57	298914,84	299169,89
Riau	42436,91	50570,46	55086,99	76864,37	70009,91	78646,29
Jambi	25332,83	45765,20	23250,08	92433,47	80275,68	90319,82
Sumatera Selatan	1074602,60	1195750,41	891760,74	553147,32	520393,48	546224,24
Bengkulu	49234,69	52099,41	54450,25	78837,91	73723,06	82891,21
Lampung	1042587,26	1174345,17	977295,88	550735,21	526509,26	550681,41
Kep. Bangka Belitung	77741,50	64767,81	177765,18	35639,14	36154,69	42139,98
Kep. Riau	93968,45	77217,79	239528,76	20070,03	19991,56	27707,25
Dki Jakarta	93310,60	77217,79	237618,55	20508,60	20209,98	27919,50
Jawa Barat	1444533,24	1164079,40	864168,76	1405062,28	1406089,58	1371861,20
Jawa Tengah	1552420,54	1197497,77	798584,74	1440366,86	1439071,11	1390751,09
Di Yogyakarta	37831,97	43144,16	10303,08	126641,64	122430,89	132769,02
Jawa Timur	1633336,01	1145513,64	770143,78	1467777,25	1456981,61	1402424,63
Banten	255141,55	486756,68	544738,52	345924,76	332114,80	355839,57
Bali	63049,53	47294,15	23037,84	115458,20	121994,04	128948,60
Nusa Tenggara Barat	157121,99	272922,78	428215,46	287595,45	296075,37	292378,02
Nusa Tenggara Timur	40024,80	93599,35	146777,26	197250,80	193636,05	203234,70
Kalimantan Barat	74890,82	178783,44	327186,36	265667,14	238412,30	265635,02
Kalimantan Tengah	9105,88	30475,75	115,27	144842,13	132041,40	138711,91
Kalimantan Selatan	178611,74	178783,44	154205,87	275096,31	253264,91	253537,00
Kalimantan Timur	42436,91	37246,80	40229,76	87170,67	79402,00	90956,56
Kalimantan Utara	86074,26	68699,38	208116,35	28841,36	27199,44	35984,84
Sulawesi Utara	52085,37	44017,84	58695,17	77741,50	74596,74	83103,46
Sulawesi Tengah	41998,35	82459,89	108148,49	189356,61	195601,83	191561,17
Sulawesi Selatan	812778,55	431277,81	299594,38	990397,88	984755,97	996610,26
Sulawesi Tenggara	22482,15	39431,00	10090,83	143087,87	137720,34	143593,57
Gorontalo	59979,56	54720,46	83740,20	65461,64	66733,60	71429,93
Sulawesi Barat	60856,70	42925,74	56572,71	84100,71	75907,27	92442,28
Maluku	68531,61	56686,24	144654,80	45287,59	44673,10	51054,31
Maluku Utara	83223,58	73504,64	205993,89	28183,51	27199,44	34286,88
Papua Barat	86732,11	73067,80	214908,23	26209,96	25670,50	33013,40
Papua	51866,09	35062,59	70793,19	68093,04	75688,85	74401,37

Table 5. Rice Productivity Prediction Results

Province	Backpropagation	Backpropagation and PSO
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*name of corresponding author



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	2024	2025	2026	2024	2025	2026
Aceh	55,88	57,72	57,57	54,96	54,58	55,94
Sumatera Utara	50,10	50,86	52,65	52,81	52,53	54,15
Sumatera Barat	48,93	51,13	51,56	50,09	50,98	53,52
Riau	44,25	51,69	52,41	41,90	44,67	48,12
Jambi	46,21	49,41	51,22	47,99	48,71	51,29
Sumatera Selatan	52,16	54,01	56,79	52,41	53,55	55,50
Bengkulu	49,48	49,10	52,01	49,37	50,95	53,12
Lampung	49,78	51,43	53,06	51,48	52,42	54,38
Kep. Bangka Belitung	41,35	45,07	49,57	37,99	44,53	47,33
Kep. Riau	29,80	33,05	40,13	29,66	36,05	37,93
Dki Jakarta	57,80	58,13	61,56	52,65	53,66	53,38
Jawa Barat	58,51	58,84	59,53	55,82	55,46	56,53
Jawa Tengah	58,86	58,72	59,44	55,65	54,98	55,97
Di Yogyakarta	50,40	51,74	52,32	50,97	52,31	53,81
Jawa Timur	57,57	58,07	59,20	55,59	55,15	56,36
Banten	48,27	52,39	56,12	52,38	52,81	55,02
Bali	59,33	60,85	61,09	56,97	56,80	57,74
Nusa Tenggara Barat	53,77	53,88	55,29	51,82	53,10	55,07
Nusa Tenggara Timur	43,63	48,81	51,70	43,05	45,50	48,37
Kalimantan Barat	31,84	34,48	38,61	31,73	37,15	39,67
Kalimantan Tengah	33,40	39,46	39,50	33,27	36,74	40,92
Kalimantan Selatan	39,59	42,36	47,22	41,48	44,19	46,68
Kalimantan Timur	32,87	35,19	45,00	38,27	42,40	45,27
Kalimantan Utara	32,10	35,71	40,29	36,32	39,75	43,81
Sulawesi Utara	42,09	47,84	50,14	42,95	45,05	48,86
Sulawesi Tengah	47,57	45,19	53,48	47,28	49,20	50,74
Sulawesi Selatan	50,64	53,60	52,07	51,47	52,39	54,11
Sulawesi Tenggara	42,66	47,01	50,78	42,70	45,44	48,06
Gorontalo	50,17	51,15	52,21	50,14	51,26	53,91
Sulawesi Barat	50,39	53,93	51,83	53,09	52,31	54,02
Maluku	41,32	53,03	49,52	41,25	43,21	46,15
Maluku Utara	35,58	43,88	43,91	42,05	40,46	46,04
Papua Barat	43,48	50,56	50,57	39,86	46,29	48,99
Papua	46,46	45,09	54,87	37,83	46,61	46,55

Table 4 and Table 5 are the prediction results for Rice Harvest Area and Productivity from 2024 to 2026. The prediction results generated using the standard Backpropagation prediction comparison with Backpropagation optimized with Particle Swarm Optimization (PSO).

DISCUSSIONS

Based on the results obtained from the test recapitulation for the harvest area and rice productivity, which can be seen in Table 2 and Table 3, it explains that the best architecture for testing the harvest area data is the 3-15-1 architecture with an MSE value of 0.0049980 for backpropagation and an MSE value of 0.00092376 for backpropagation with PSO optimization. From these results, it can be explained that using backpropagation with PSO optimization is better than standard backpropagation with a smaller MSE value on the data of harvested area. The best architecture for testing rice productivity data is the 3-15-1 architecture with an MSE value of 0.0049998 for backpropagation and an MSE value of 0.000435762 for backpropagation with PSO optimization. From these results, it can be explained that using backpropagation with PSO optimization is better than standard backpropagation with a smaller MSE value on rice productivity data. Furthermore, Table 4 and Table 5 explain the prediction results of the harvest area and rice productivity from 2024 to 2026 with standard backpropagation and backpropagation with PSO optimization. By using PSO optimization, the results obtained are that some provinces have increased and some have decreased, and slightly different values of increase and decrease with ordinary backpropagation. For this reason, the results of backpropagation with PSO optimization are the best results because the accuracy produced when testing is 100% for the data of rice harvest area and rice productivity, and the MSE value is smaller.

CONCLUSION

The conclusion of this research is that the Backpropagation method with Particle Swarm Optimization optimization is better than ordinary Backpropagation. This is because the resulting MSE value is less and the accuracy is better than the usual Backpropagation. The MSE value using PSO optimization on the Harvest Area is 0.00092376 with 3-15-1 architecture. The MSE value using PSO optimization on Rice Productivity is 0.000435762 with 3-15-1 architecture. The prediction results obtained by Particle Swarm Optimization (PSO) optimization show an increase and a decrease in some provinces in Indonesia from 2024 to 2026, and these results show more consistent and accurate results. For this reason, the results of this study can be useful for the Government, farmers, researchers and policy makers for more effective agricultural planning and better risk management.

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