

Bird Sound Quality Analysis for Chirping Masters Using Mel Frequency Cepstrum Coefficiens (MFCC) and Svm Classification Algorithm


Almeranda Haryaveda Nurul Zahron¹, Rakhmat Kurniawan¹

¹ Computer Science Study Program, Faculty of Science and Technology, State Islamic University of North Sumatra, Indonesia

ABSTRACT

Birds play an important role in ecosystems as indicators of environmental health and biodiversity. In Indonesia, there are approximately 1,531 bird species, including songbirds that are popular for their melodious chirps. Bird sounds are used for communication, territorial marking, and are a key attraction in bird song competitions. However, obtaining a bird with high-quality vocalization requires specific training, one of which is the mastering method using recordings of champion bird songs. Additionally, the Support Vector Machine (SVM) algorithm has proven effective in classifying bird species based on sound, achieving 77% accuracy after noise reduction. The combination of MFCC and SVM allows for more systematic and accurate analysis of bird vocalizations. This research is expected to contribute to the field of ornithology, the development of songbird husbandry techniques, and serve as a guide for bird enthusiasts in selecting high-quality master bird sounds.

Keyword : Songbirds; Bird Classification; MFCC; SVM; Chirping Masters, Bird Sounds.

 This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Corresponding Author:

Rakhmat Kurniawan,
Faculty of Science and Technology, State Islamic University of North Sumatra,
Indonesia
Jln. Lapangan Golf, Desa Durin Jangak, Kec. Pancur Batu, Kabupaten Deli Serdang –
Sumatera Utara 20353
Email : rakhmat.kr@uinsu.ac.id

Article history:

Received Aug 15, 2025
Revised Aug 30, 2025
Accepted Sep 3, 2025

1. INTRODUCTION

Birds are natural predictors of animal diversity and ecosystem preservation worldwide. Birds play a vital role in ecosystems, serving as indicators of environmental health and contributing to biodiversity (Gokkon, 2022). There are approximately 9,200 bird species worldwide. Indonesia has approximately 1,531 bird species, some of which are songbirds or chirping birds (Amjad, Shahid, & Ali, 2024).

One of the main attractions of birds is their ability to produce unique sounds called chirps. Birds use chirps to communicate with each other, attracting mates, marking territory, and warning of danger. Because of their melodious chirps, people keep and breed them for their own enjoyment (Alhasni, 2020). As birds evolve, they are no longer simply kept in cages and enjoyed by families. They can also be entered into competitions, competing for rhythm, song, volume, stamina, or duration of song, and physical beauty. Currently, bird song assessments are generally based on visual and auditory appearance, leading to differing opinions on the quality of a bird's voice.

However, obtaining a bird with a melodious voice is quite difficult. This requires training and providing nutritious food to improve the bird's vocal quality. One such training method is listening to master birdsong, which involves listening to and using high-quality birdsong as a reference or training tool for pet birds. Master birds can be trained birds, birds that frequently participate in contests or have won, or audio recordings of birdsong. By listening to quality birdsong, pet birds can imitate and improve the variety and beauty of their own voices (Ali, 2020).

Several studies related to the identification and classification of bird sounds have been conducted for a long time. One of them, according to (Ramashini, Abas, & Mohanchandra, 2021), this study focused on developing robust features for bird sound classification. The results showed that the GTCC feature-based classification outperformed LPCC and MFCC, with an accuracy of 93.3%. This study also noted that combining the three cepstral features did not improve accuracy compared to using the GTCC feature alone.

In addition, for the classification of bird sounds used is the Support Vector Machine (SVM) algorithm has been proven effective in classifying data based on the extracted features. Based on research (Afida, 2020) revealed that the Support Vector Machine (SVM) algorithm can be used effectively to classify bird species based on their sounds. In the study of bird species classification based on sounds using 5 species of birds with a noise reduction process first. The results of the sound signal that has been reduced noise produces a clearer sound signal with a PSNR of 4.2890. Classification using SVM Kernel Heavy Tailed RBF and a ratio of 7: 3 produces an accuracy of 77.00%. The success of using SVM shows that choosing the right feature extraction focus can increase accuracy in bird song analysis.

The combination of MFCC and SVM allows for systematic and accurate analysis of bird song quality. This research is expected to significantly contribute to the field of ornithology and the development of songbird husbandry techniques, as well as provide guidance for bird lovers in selecting the best sounds for master songbirds. It is also hoped that this research will provide a deeper understanding of the characteristics of bird song.

2. RESEARCH METHOD

2.1 Mel-Frequency Cepstral Coefficients

MFCC is the most frequently used sound extraction technique in various fields of sound processing, as it is considered quite good at representing signals. According to (Putra & Nurdiansyah, 2024), to extract sound features, the Mel-Frequency Cepstral Coefficients algorithm is often used. This algorithm transforms sound representations from time to frequency, using the concept of divide and conquer, making MFCC very efficient in processing digital sound signals (Budiman, 2020).. In speech recognition, MFCC is used to analyze sounds by imitating the human ear's ability to distinguish sounds based on frequency, to extract important features from the sound.

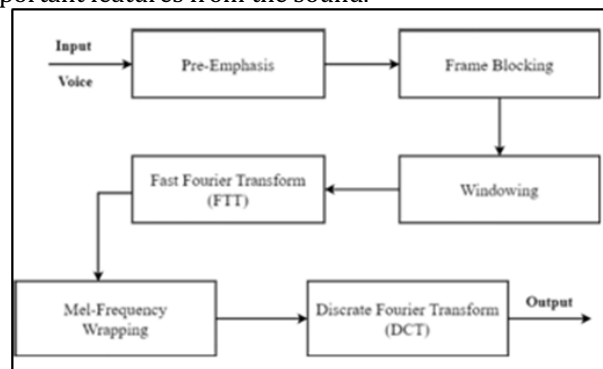


Figure 1. Block diagram of the MFCC method process

The MFCC process consists of pre-emphasis, frame blocking, windowing, fast Fourier transform, Mel frequency warping, and discrete cosine transform. The block diagram of the MFCC process can be visualized as shown in Figure 1.

1. Pre-Emphasis

The purpose of this filtering is to obtain a smoother frequency spectral shape of the speech signal. The pre-emphasis filter is based on the input/output relationship in the time domain, which is expressed in the following equation:

$$y(n) = x(n) - \alpha \cdot x(n - 1)$$

Description:

$y(n)$: output signal.

$x(n)$: input signal.

α : pre-emphasis coefficient (usually between 0.95 and 0.97).

n : time index

2. Frame Blocking

In this process, the audio signal is segmented into several overlapping frames. This process ensures that no part of the signal is lost.

3. Windowing

The windowing process aims to minimize signal discontinuity at the beginning and end of each frame. If we define the window as $w(n)$, $0 \leq n \leq N - 1$, where N is the number of samples in each frame, then the result of windowing is the signal:

$$w(n) = x(n)h(n), 0 \leq n \leq N - 1$$

where $w(n)$ usually uses the Hamming window which has the form:

$$h(n) = 0.54 - 0.46 \cdot \cos\left(\frac{2\pi n}{N-1}\right), 0 \leq n \leq N - 1$$

4. Fast Fourier Transform (FFT)

FFT is a fast algorithm of Discrete Fourier Transform (DFT) which is a useful process for converting each frame with N samples from the time domain to the frequency domain, as defined as follows:

$$X(k) = \sum_{n=0}^{N-1} w(n) e^{-2\pi jkn/N}$$

Description:

$X(k)$: Frequency spectrum.

$w(n)$: Windowed signal.

N : Frame length.

j : Imaginary number.

k : Frequency index.

5. Mel-frequency wrapping

The mel-frequency scale is a linear low frequency scale below 1000 Hz and a logarithmic high frequency scale above 1000 Hz (Nurarinda, Sahertian, & Mahdiyah, 2020). The following equation shows the relationship between the mel scale and frequency in Hz:

From frequency (f) to Mel (m):

$$m = 2595 \times \log_{10}(1 + f/700)$$

From Mel (m) to frequency (f):

$$f = 700 \times (10^{(m/2595)} - 1)$$

6. Discrete Cosine Transform (DCT)

The Cosine Transform (DCT) is used to convert the frequency spectrum into a cepstrum. The cepstrum is the inverse of the spectrum. The phonetic characteristics of a speech signal are not lost after being converted to cepstrum form. The result is called the mel-frequency cepstrum coefficient (MFCC). The following is the equation used:

Calculate the spectrum energy:

$$E(k) = |X(k)|^2$$

Apply the Mel filter to obtain the Mel spectrum:

$$M(m) = \sum_k E(k) \cdot H_m(k)$$

Where $H_m(k)$ is the response of the Mel filter.

Take the logarithm of the Mel spectrum:

$$\log M(m)$$

Apply DCT to the log Mel spectrum to obtain the MFCC coefficients:

$$C(k) = \sum_{n=0}^{M-1} \log M(n) \cdot \cos\left[\frac{\pi}{M}\left(n + \frac{1}{2}\right)k\right], k = 0, 1, \dots, K - 1$$

Typically, only the coefficients $C(k)$ for $k = 0$ to $K - 1$ are taken as the MFCC.

2.2 Support Vector Machine

Support vector machines work by identifying the best hyperplane that separates data into two classes. This hyperplane, which can be a two-dimensional line or a three-dimensional plane, is surrounded by support vectors, the data points closest to the hyperplane (Sriani & Hasibuan, 2022). SVMs attempt to maximize the margin, the distance between the hyperplane and the nearest support vectors, to improve model generalization (Ramon & Nazir, 2022). Finding the best hyperplane requires finding a hyperplane between two bounding classes, and finding the best hyperplane requires maximizing the margin between two objects of dissimilar classes. The hyperplane value can also be formulated as follows:

$$x_i \cdot w + b \geq +1, y_i = +1$$

$$x_i \cdot w + b \leq -1, y_i = -1$$

Description:

w : weight vector.

x_i : feature vector for the i -th data point.

b : bias.

y_i : class label of the i -th data point.

2.3 Confusion Matrix

A confusion matrix is a tool used to evaluate the performance of a classification model in machine learning. This matrix provides an overview of the number of correct and incorrect predictions made by the model, allowing for a more in-depth analysis of the classification results.

The confusion matrix consists of four main elements:

- True Positive (TP): The number of correct positive predictions. The model predicts the positive class and it is the correct class.
- True Negative (TN): The number of correct negative predictions. The model predicts the negative class and it is also correct.
- False Positive (FP): The number of incorrect positive predictions. The model predicts the positive class, but the actual class is negative. This is known as a "Type I error."
- False Negative (FN): The number of incorrect negative predictions. The model predicts the negative class, but the actual class is positive. This is known as a "Type II error."

The accuracy, f1-score, precision, and recall of the model can be assessed using the confusion matrix value. The match between the weighted average precision and recall is described by the f1-score (Sapitri, 2022).

3. RESULTS AND DISCUSSION

A. Data Collection

For each data set, recording was performed two to three times to ensure the data obtained was truly reliable and suitable for research. A total of 72 data sets were used from 24 birds, divided into six different birds of each species.

Table 1. Bird sound training data

Number of Birds	Types of birds	Number of Votes
4	Murai Batu	12
4	Kacer	12
4	Cucak Ijo	12
4	Lovebird	12

Table 2. Bird sound testing data

Number of Birds	Types of birds	Number of Votes
2	Murai Batu	6
2	Kacer	6
2	Cucak Ijo	6
2	Lovebird	6

B. MFCC Extraction

The Mel-Frequency Cepstral Coefficients (MFCC) method is a series of mathematical steps to transform an audio signal into a representation that is more easily analyzed by a machine learning model. The resulting MFCC coefficients typically only take the first 12-13 coefficients, as higher coefficients tend to be less significant. Of the 72 sound data that have been extracted, the following is a display of 4 MFCC extracted data representing each bird.

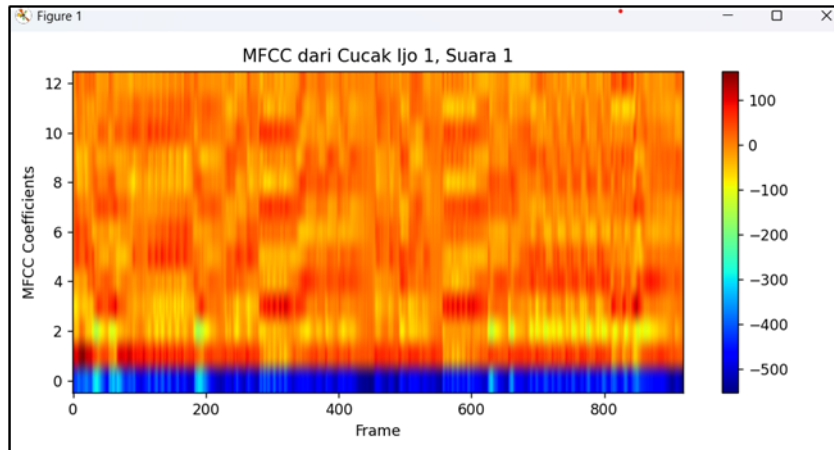


Figure 2. MFCC of Cucak ijo

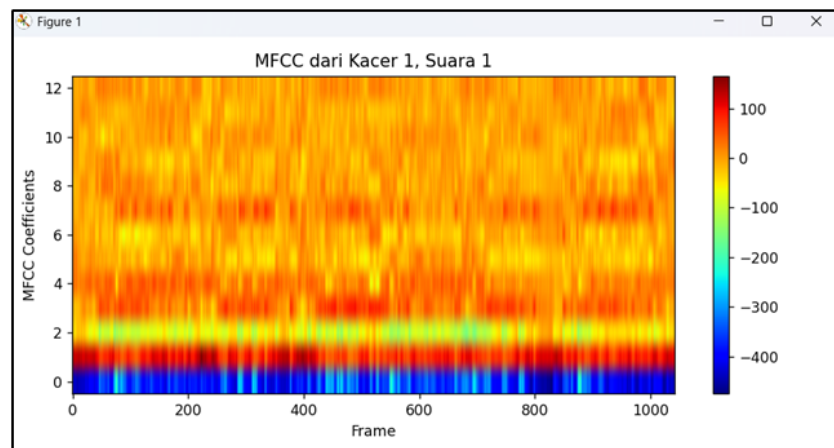


Figure 3. MFCC of Kacer

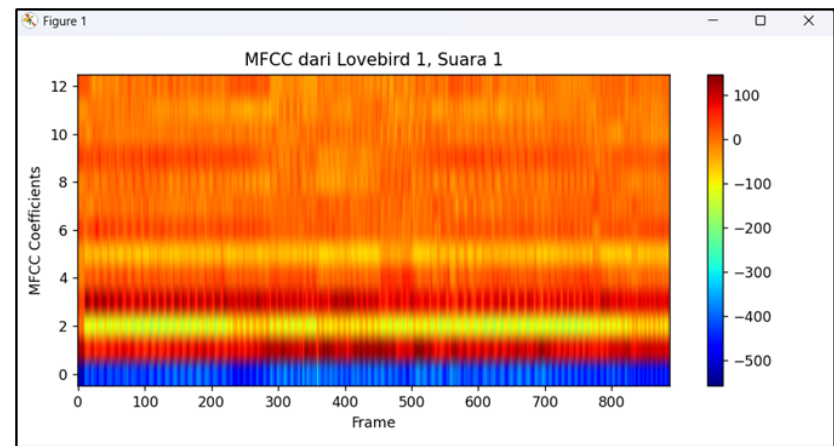


Figure 4. MFCC of Lovebird

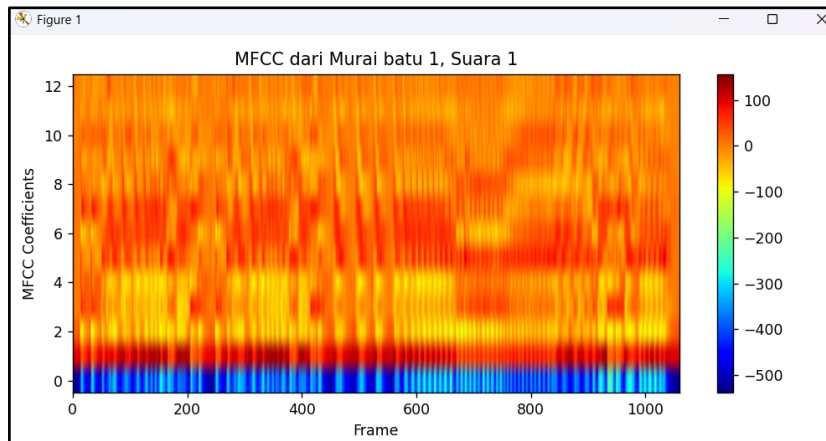


Figure 5. MFCC of Murai batu

From the MFCC results data that has been provided previously, here is all the data that has been extracted which can be seen in Figure 6 and 7.

ukuran DataFrame: (72, 15)															
	MFCC_1	MFCC_2	MFCC_3	MFCC_4	MFCC_5	MFCC_6	MFCC_7	MFCC_8	MFCC_9	MFCC_10	MFCC_11	MFCC_12	MFCC_13	jenis_burung	kualitas
0	-419.81	89.72	-104.29	84.21	17.03	-55.35	16.14	0.95	-6.64	14.15	-7.41	-19.00	-5.73	Lovebird	1
1	-416.96	78.16	-88.98	84.62	19.99	-46.05	19.90	14.88	-8.35	15.07	-8.26	-13.96	6.07	Lovebird	1
2	-410.38	85.85	-100.22	73.49	26.57	-49.55	17.82	11.71	-2.60	17.21	-5.00	-16.83	1.40	Lovebird	1
3	-410.79	84.38	-111.53	64.05	20.63	-11.20	-13.47	3.13	14.94	9.12	12.41	-26.55	-9.22	Lovebird	1
4	-418.06	88.77	-98.86	66.21	18.99	-12.39	-9.85	2.47	12.24	4.24	16.63	-22.29	-13.90	Lovebird	1
5	-393.63	78.18	-98.05	63.97	3.44	-16.13	-5.25	0.87	14.92	6.20	7.52	-9.42	-9.38	Lovebird	1
6	-388.78	82.05	-115.13	77.23	8.68	-10.16	7.95	0.96	2.68	-0.13	24.54	-9.75	-14.10	Lovebird	1
7	-401.76	73.48	-115.08	70.87	6.48	-16.25	5.93	0.31	-0.06	-3.32	26.67	-10.16	-18.26	Lovebird	-1
8	-399.79	75.31	-112.52	70.69	5.46	-18.80	7.06	3.56	0.67	-4.71	26.66	-7.68	-17.97	Lovebird	1
9	-402.60	69.96	-111.92	67.80	27.86	-37.65	-3.97	23.79	12.67	-4.12	11.18	-16.56	-10.61	Lovebird	-1
10	-429.18	91.42	-95.65	82.88	10.40	-35.01	1.05	31.15	11.83	-11.08	13.64	-20.89	-6.36	Lovebird	1
11	-428.35	74.62	-104.19	71.59	12.08	-33.17	2.70	11.11	2.60	9.59	12.42	-37.76	-7.02	Lovebird	1
12	-435.07	80.29	-96.66	85.72	15.30	-27.73	-6.14	17.34	-5.74	-0.19	11.83	-22.95	-10.28	Lovebird	-1
13	-434.52	62.00	-103.98	88.21	10.86	-24.59	-10.19	18.31	-7.77	2.17	14.35	-23.38	-6.19	Lovebird	-1
14	-435.65	62.97	-104.52	83.41	12.66	-25.77	-8.36	16.37	-9.35	2.25	13.79	-23.93	-7.04	Lovebird	-1
15	-408.51	96.85	-118.79	23.95	37.15	-39.63	5.89	20.52	-11.23	5.95	14.49	-5.29	-12.04	Lovebird	1
16	-426.28	90.96	-110.65	57.67	26.39	-13.31	-7.00	8.12	3.65	-11.82	7.46	-3.58	-17.56	Lovebird	-1
17	-426.85	83.25	-116.42	72.90	8.05	-18.58	-13.61	14.32	14.12	-3.94	7.15	-23.66	-15.78	Lovebird	-1
18	-454.15	44.68	-45.69	5.89	17.78	9.00	-4.54	9.05	-0.52	0.83	12.01	-6.88	-5.50	Cucak_ijo	1
19	-461.13	39.35	-35.99	2.10	10.75	9.99	-5.76	4.43	4.96	-1.58	5.10	-6.23	-0.74	Cucak_ijo	1
20	-417.11	37.60	-51.70	15.20	7.81	7.47	-5.94	4.06	-7.35	4.24	16.20	-13.51	-9.76	Cucak_ijo	1
21	-347.34	58.42	-95.94	42.16	15.72	3.43	-1.19	-17.11	2.33	12.25	11.88	-10.36	-13.33	Cucak_ijo	1
22	-386.36	52.74	-92.95	32.34	24.26	0.04	-3.14	14.05	8.70	-17.48	10.29	9.96	-11.24	Cucak_ijo	1
23	-324.40	51.48	-86.33	52.27	3.14	-2.87	-1.57	-15.76	-0.71	9.31	16.59	-20.70	-18.43	Cucak_ijo	-1
24	-380.42	61.47	-71.27	-1.33	44.93	9.79	-24.01	-2.20	16.88	4.01	-2.71	-1.19	-3.66	Cucak_ijo	-1
25	-354.49	79.42	-64.09	-17.34	19.67	11.29	-18.82	-6.11	1.90	-11.65	-3.92	-3.66	-4.22	Cucak_ijo	-1
26	-367.63	77.92	-63.18	-14.43	30.96	19.89	-18.70	1.46	12.07	-10.92	-2.68	-4.01	-8.98	Cucak_ijo	-1
27	-374.18	129.38	-58.66	-14.39	34.05	11.21	-9.67	-6.68	5.92	11.22	3.77	-10.59	-12.45	Cucak_ijo	-1
28	-357.42	112.08	-77.76	0.48	30.72	1.40	-7.45	-1.55	3.32	3.20	7.47	-9.07	-16.11	Cucak_ijo	-1
29	-392.67	130.49	-61.96	-4.86	30.50	-6.58	-14.49	7.94	10.20	-4.53	0.52	-3.37	-12.44	Cucak_ijo	-1
30	-420.92	104.06	-19.97	-8.86	18.38	7.17	-7.81	-6.92	-1.74	6.87	4.13	-12.32	-9.77	Cucak_ijo	-1
31	-432.16	108.35	-18.77	-10.77	18.12	18.01	-6.17	-11.89	-7.54	7.03	8.40	-13.23	-7.54	Cucak_ijo	-1
32	-407.86	89.66	-25.06	20.77	8.62	-10.40	-0.32	13.31	-6.98	-7.49	4.60	-0.35	-3.73	Cucak_ijo	-1
33	-472.84	106.06	-55.46	34.28	10.29	-16.89	8.02	-3.12	-10.27	10.53	9.76	-18.25	-6.56	Cucak_ijo	-1
34	-455.71	92.65	-82.47	35.90	20.82	-19.65	4.05	-3.23	-8.91	13.04	8.54	-21.87	-9.76	Cucak_ijo	-1
35	-502.68	131.11	-59.27	60.13	12.26	-16.05	8.11	8.35	-16.46	7.90	15.31	-21.44	-14.11	Cucak_ijo	-1
36	-370.39	87.25	-73.38	33.09	21.03	-16.05	-15.14	18.67	-2.27	-11.33	-4.31	-6.45	-0.34	Kacer	-1
37	-302.08	53.69	-101.27	43.55	17.99	-12.11	-21.37	14.83	-6.06	-1.78	-0.73	-10.73	1.59	Kacer	-1
38	-310.83	70.09	-80.35	32.66	8.65	-16.35	-14.39	14.30	-10.49	-6.57	-0.66	-9.96	-3.72	Kacer	-1

Figure 6. MFCC result dataframe

39	-362.76	70.24	-63.23	20.07	6.60	13.65	-16.02	10.52	2.12	-4.24	5.06	-8.54	-4.20	Kacer	1
40	-325.13	59.33	-65.08	31.23	1.13	7.29	-10.02	24.27	-3.80	-7.00	11.34	-9.13	-7.95	Kacer	-1
41	-393.04	59.90	-73.99	15.02	12.69	10.39	-21.24	7.06	4.96	-4.31	2.39	-9.60	-3.19	Kacer	-1
42	-360.10	101.92	-86.64	21.05	12.32	1.76	-12.63	9.75	-1.87	-0.18	-0.05	-5.18	-1.12	Kacer	-1
43	-291.70	68.36	-84.92	40.53	2.97	-1.07	-10.94	-1.24	4.93	-3.31	-0.54	-8.33	-14.26	Kacer	-1
44	-351.28	76.75	-86.39	34.55	9.10	-2.58	-15.37	9.57	-1.35	-2.80	-2.95	-7.13	-3.26	Kacer	-1
45	-358.25	91.94	-75.23	17.47	14.63	-6.44	-22.32	4.14	10.15	-8.00	-6.08	1.99	-7.63	Kacer	-1
46	-399.99	83.89	-77.32	47.60	21.06	-7.90	-23.93	6.66	11.23	-6.37	-6.70	-3.47	3.11	Kacer	-1
47	-416.28	73.51	-71.32	43.68	17.67	-8.55	-19.18	7.17	3.40	-0.57	-4.75	-8.41	0.29	Kacer	-1
48	-333.06	71.89	-79.31	16.67	18.44	-0.46	-6.85	-9.27	-1.62	1.27	-1.19	-3.84	-0.56	Kacer	-1
49	-348.74	74.89	-67.07	24.89	14.47	-7.17	-12.46	-6.62	5.34	-2.05	0.52	-5.83	-12.47	Kacer	-1
50	-370.10	95.20	-39.95	9.92	12.83	-14.53	-15.10	4.27	6.14	-10.76	-2.49	4.83	-7.35	Kacer	-1
51	-294.25	61.22	-95.19	40.18	-17.45	-26.07	8.42	-3.94	11.32	3.03	-10.12	2.10	-12.78	Kacer	-1
52	-268.31	71.90	-93.23	55.04	-9.47	-21.40	8.35	0.18	12.24	2.16	-9.14	0.79	-10.40	Kacer	-1
53	-224.12	45.00	-128.65	40.39	-25.73	-4.15	-11.75	16.96	4.82	7.46	4.44	-12.36	-11.26	Kacer	-1
54	-386.49	85.70	-42.73	-7.24	-27.19	30.68	19.90	22.14	-6.11	-4.10	3.59	-15.07	-1.20	Murai_batu	-1
55	-319.09	120.41	-52.66	23.42	-30.38	29.31	2.07	20.30	-11.12	8.81	5.90	-15.87	-0.29	Murai_batu	-1
56	-310.59	117.27	-73.24	-20.41	-31.44	8.86	19.82	15.76	6.78	-3.87	0.94	-12.34	-4.53	Murai_batu	-1
57	-315.55	119.44	-58.70	-24.06	-14.25	26.16	-5.27	8.44	-6.63	-9.96	10.13	-5.52	-3.16	Murai_batu	-1
58	-371.53	122.87	-42.01	-42.89	-17.13	39.58	-0.03	7.62	-4.05	-6.00	3.52	-12.45	-6.70	Murai_batu	-1
59	-363.40	96.46	-48.25	-19.58	-7.76	41.38	-2.46	1.48	-1.69	-7.62	4.73	-3.47	-4.67	Murai_batu	-1
60	-353.72	116.96	-51.03	-34.75	-19.39	32.65	6.68	9.29	5.93	-11.37	-0.72	-2.78	-10.01	Murai_batu	-1
61	-343.00	98.88	-48.66	-16.91	-17.55	39.19	1.66	6.13	3.20	-5.23	5.31	-7.33	-7.89	Murai_batu	-1
62	-350.95	110.48	-44.98	-23.77	-21.69	33.54	1.68	5.50	6.55	-9.97	-0.49	-3.86	-6.51	Murai_batu	-1
63	-350.24	85.50	-60.59	10.89	-1.84	5.97	-1.88	8.27	3.81	-11.44	0.53	-7.26	-6.95	Murai_batu	-1
64	-328.24	97.00	-65.14	9.77	-1.57	8.77	-1.92	17.69	0.00	-22.18	19.02	-7.24	-6.00	Murai_batu	-1
65	-347.63	91.37	-57.00	12.93	2.77	10.05	0.23	20.36	0.99	-19.98	19.77	-1.96	-6.70	Murai_batu	1
66	-335.95	69.23	-75.02	28.45	14.33	3.82	-9.56	7.86	8.95	-6.86	0.91	-1.73	-2.00	Murai_batu	1
67	-296.42	68.54	-108.21	50.27	-2.87	8.39	10.07	13.54	-3.32	-10.56	8.99	-6.23	6.11	Murai_batu	-1
68	-319.74	68.87	-90.92	49.01	-10.32	-3.82	7.77	11.70	-7.07	-8.24	6.78	-6.56	4.26	Murai_batu	-1
69	-309.62	31.12	-79.20	53.82	-8.31	-2.94	-6.41	6.61	-1.21	-15.88	27.01	-10.00	-10.02	Murai_batu	-1
70	-316.66	39.83	-92.01	74.35	-8.84	-9.97	-17.47	18.29	7.94	-29.36	23.29	-6.76	-4.55	Murai_batu	-1
71	-314.36	56.89	-94.99	14.22	16.45	11.99	-17.09	-2.08	1.28	-16.43	19.97	-1.23	-15.18	Murai_batu	-1

Figure 7. MFCC result dataframe (continued)

C. Classification of SVM

```

jenis_burung  kualitas
Cucak_ijo     -1      11
              1      7
Kacer         -1     15
              1      3
Lovebird      1     10
              -1      8
Murai_batu    -1     14
              1      4
Name: count, dtype: int64
    
```

Figure 8. Data distribution

From the picture above, it can be seen that the number of good quality green cucak is 7 and the number of less good quality is 11, in kacer, there are only 3 good quality and less good quality is 15, while lovebirds have 8 good quality and 10 less good quality, and finally the magpie robin has 4 good sound quality and 14 less good quality.

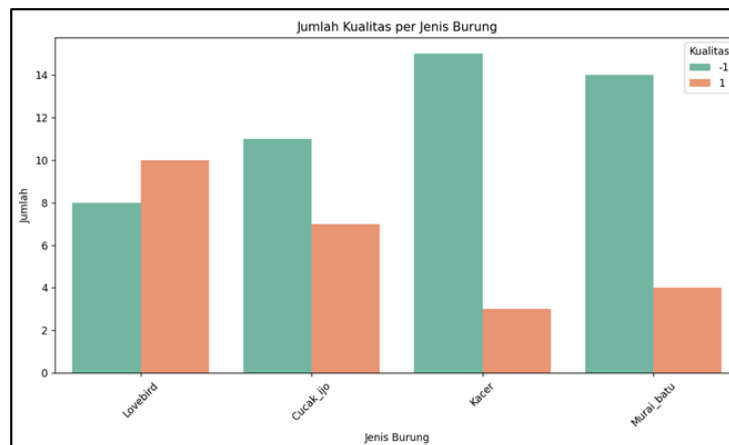


Figure 9. Comparison chart of the number and quality of bird sounds

From the graph above, it can be seen that lovebirds have the highest good sound quality and the lowest bad sound quality, while kacer has the opposite.



Figure 10. Bird sound quality percentage graph

From the graph, it can be seen that the ratio of the total number of good votes to bad votes is 1/3.

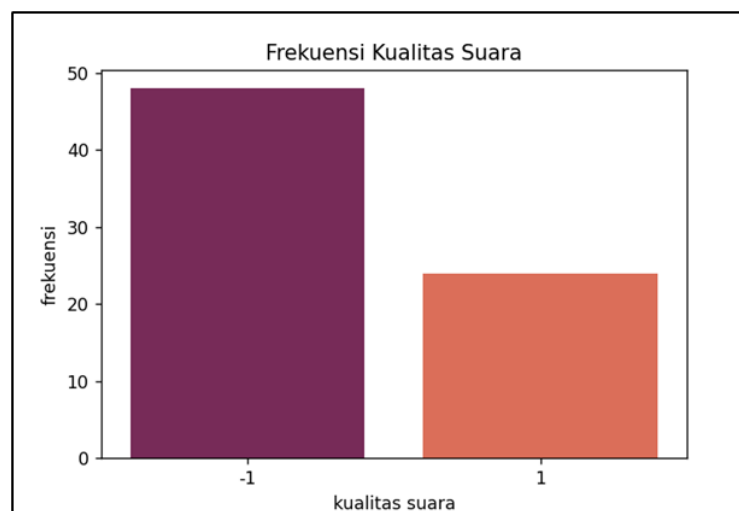


Figure 11. Bird sound quality frequency graph

From the graph above, it can be seen that the sound quality of birds that are not good almost reaches 50, while the sound quality of birds that are not good does not reach 30.

D. Confussion Matrix

Through this testing process, this study aims to evaluate the effectiveness of the SVM model in classifying various types of bird calls based on MFCC features. This study will also identify the strengths and limitations of the SVM model in the context of bird call classification and provide insights into how the model can be improved.

	precision	recall	f1-score	support
Cucak_ijo	0.75	0.75	0.75	8
Kacer	0.83	0.71	0.77	7
Lovebird	0.89	1.00	0.94	8
Murai_batu	0.83	0.83	0.83	6
accuracy			0.83	29
macro avg	0.83	0.82	0.82	29
weighted avg	0.83	0.83	0.82	29

Akurasi SVM: 82.76%

Figure 12. Accuracy results

The Classification Report results show important metrics for assessing model performance, namely Precision, Recall, and F1-Score for each analyzed sound class. The model's overall accuracy was 82.76%. This indicates that the SVM model correctly predicted approximately 82.76% of all examples in the test data.

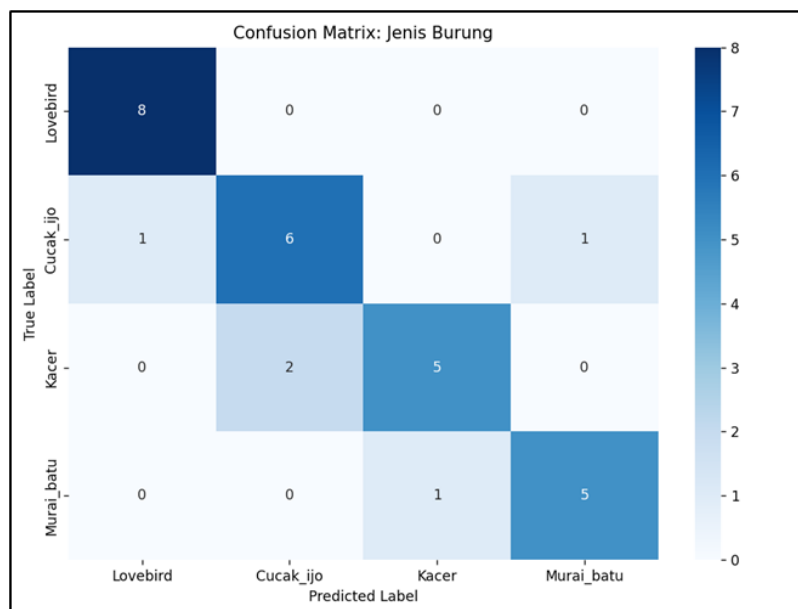


Figure 13. Confusion Matrix

The displayed confusion matrix provides a clear picture of the SVM model's prediction results in classifying bird species. The X-axis shows the model's predicted labels: Lovebird, Cucak_ijo, Kacer, and Murai_batu, while the Y-axis shows the actual labels from the test data. Each cell in the matrix indicates the number of predictions within a specific category.

4. CONCLUSION

The MFCC extraction results demonstrate its high effectiveness in extracting signals from bird songs. This allows for more specific identification of the values of each component and its quality. Test results using a 60:40 ratio (60% training data and 40% test data) indicate that the SVM model achieved optimal prediction accuracy, with a maximum accuracy of 100% and a minimum accuracy of 75%. This model's performance demonstrates that the SVM model can be used effectively to differentiate between various types of bird songs. The model's success in achieving the highest level of accuracy demonstrates its ability to identify the unique patterns and characteristics of each type of bird song. The test results demonstrate that the SVM model has significant potential for classifying bird songs. The model's accuracy, with 40% training data, demonstrates its ability to identify and differentiate bird songs with a high accuracy of 82.76%.

REFERENCES

- Abdurrazaq, N., & Prasetyawan, Y. Y. (2022). ANALISIS KEBUTUHAN INFORMASI BAGI PECINTA BURUNG KICAU DI KOTA PEMALANG. *Jurnal Ilmu Perpustakaan*.
- Afida, A. M. (2020). KLASIFIKASI JENIS BURUNG BERDASARKAN SUARA MENGGUNAKAN ALGORITME SUPPORT VECTOR MACHINE. *Jurnal Ilmiah Matematika*, 1-6.
- Alhasni, A. F. (2020). RANCANG BANGUN APLIKASI DATABASE BURUNG KICAU BERBASIS ANDROID. Solo: UNIVERSITAS MUHAMMADIYAH SURAKARTA.
- Ali, M. F. (2020). KLASIFIKASI JENIS BURUNG BERDASARKAN SUARA BURUNG BERBASIS DEEP LEARNING . Surabaya: Institut Teknologi Sepuluh Nopember .
- Amjad, S. H., Shahid, D., & Ali, W. (2024). Birds' Sound Classification Using Acoustic Signals. *Technical Journal, University of Engineering and Technology (UET)*, 53-60.
- Armansyah, & Suhardi. (2025). MODEL REGRESI LOGISTIK DAN JARINGAN SYARAF TIRUAN UNTUK KLASIFIKASI MAHASISWA BERPOTENSI DROP OUT. *Jurnal Teknoif Teknik Informatika Institut Teknologi Padang*, 8-16.
- Budiman, F. (2020). PENGENALAN SUARA BURUNG MENGGUNAKAN MEL FREQUENCY CEPSTRUM COEFFICIENT DAN JARINGAN SYARAF TIRUAN PADA SISTEM PENGUSIR HAMA BURUNG. *Jurnal Nasional Teknik Elektro*, 64-72.
- Chyan, P. (2024). *Pengantar Machine Learning*. Deli Serdang: PT. MIFANDI MANDIRI DIGITAL.
- Dinuriyati, I. S. (2023). Klasifikasi Pengenal Suara Kicau Burung Menggunakan Metode Linear Predictive Coding (LPC) Dan Nearest Neighbor. Malang: Centra Library Of Maulana Malik Ibrahim State Islamic University Of Malang.
- Gokkon, B. (2022, September 29). Pentingnya Big Data, Memantau Perdagangan Online Burung Kicau di Indonesia. Retrieved from Mongabay: <https://www.mongabay.co.id/2022/09/29/pentingnya-big-data-memantau-perdagangan-online-burung-kicau-di-indonesia/>
- Milal, I. S., & Hasanudin, M. (2023). KLASIFIKASI TEKS REVIEW PADA E-COMMERCE TOKOPEDIA MENGGUNAKAN ALGORITMA SVM. *Jurnal Ilmiah Nasional Riset Aplikasi dan Teknik Informatika* , 34-45.
- Müller, A., & Guido, S. (2016). *Introduction to Machine Learning with Python*. O'Reilly Media.
- Nanda, R., & Haerani, E. (2022). Klasifikasi Berita Menggunakan Metode Support Vector Machine . *Jurnal Nasional Komputasi dan Teknologi Informasi* , 269-278.
- Nurarinda, T. A., Sahertian, J., & Mahdiyah, U. (2020). Rancangan Sistem Identifikasi Jenis Burung Kicau Berdasarkan Suara Burung dengan Mel Frequency Cepstrum Coefficiens (MFCC). *Seminar Nasional Inovasi Teknologi* , 237-441.
- Prapcoyo, H., Putra, B. P., & Perwira, R. I. (2021). IMPLEMENTATION OF MEL FREQUENCY CEPSTRAL COEFFICIENT AND DYNAMIC TIME WARPING FOR BIRD SOUND CLASSIFICATION. *Prosiding Seminar Nasional Teknologi Informasi dan Kedirgantaraan*, 139-147.
- Putra, R. M., & Nurdiansyah, F. (2024). Klasifikasi Jenis Burung Cucak Berdasarkan Suara Menggunakan MFCC Dan Naive Bayes . *JURNAL FASILKOM* , 463-470 .
- Rafiqah, I. N. (2024). Klasifikasi Kelayakan Mutu Crude Palm Oil Menggunakan Algoritma Support Vector Machine. Medan: Universitas Islam Negeri Sumatera Utara .
- Ramashini, M., Abas, E., & Mohanchandra, K. (2021). Robust cepstral feature for bird sound classification . *International Journal of Electrical and Computer Engineering (IJECE)* , 1477~1487 .
- Ramon, E., & Nazir, A. (2022). KLASIFIKASI STATUS GIZI BAYI POSYANDU KECAMATAN BANGUN PURBA MENGGUNAKAN ALGORITMA SUPPORT VECTOR MACHINE (SVM). *Jurnal Sistem Informasi dan Informatika (Simika)*, 143-150.
- Sanjaya, M., & Salleh, Z. (2020). IMPLEMENTASI PENGENALAN POLA SUARA MENGGUNAKAN MEL-FREQUENCY CEPSTRUM COEFFICIENTS (MFCC) DAN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) SEBAGAI KONTROL LAMPU OTOMATIS. *Al-HAZEN Journal of Physics*, 43-54.
- Sapitri, B. (2022). Klasifikasi Rumah Layak Huni Menggunakan Algoritma Support Vector Machine. Medan: Universitas Negeri Islam Sumatera Utara.