IMPLEMENTATION MFCC (MEL FREQUENCY CEPSTRAL COEFFICIENT) AND NAIVE BAYESIAN METHOD FOR CLASSIFICATION BASIC TONE GUITAR

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ABSTRACT

The guitar is a musical instrument of modern popular and widely used as a filling instrument rhythm and melody in a song. Chord or chord knowledge necessary to play the guitar. Akor is a series of tones that build on the harmonization of music [9]. Recognizing a guitar chord is more difficult for the human auditory sense, especially for those new to the guitar chord.This study uses MFCC (Mel Frequency cepstral coefficient) for the extraction of voice and Naive Bayesian classification. MFCC method is a feature extraction technique that has been widely used in voice signal processing, especially on the introduction of the speaker. MFCC methods have specific characteristics to be extracted from the input voice signal which will be recognized.

Based on the research that has been done can be seen classification of basic guitar tone with Naïve Bayesian classification using MFCC method as a method for the extraction of voice processing and naive Bayesian method as a method of classification. From the testing that has been done classification of basic guitar tones using MFCC and naive Bayesian method obtained an accuracy level of 70%.

Keywords: Tones Guitar, Mel Frequency cepstral coefficient, Naive Bayesian Artificial Intelligence.

1. PRELIMINARY

The guitar is a musical instrument of modern popular and widely used as a filling instrument rhythm and melody in a song. Chord or chord knowledge necessary to play the guitar. Akor is a series of tones that build on the harmonization of music [9]. Recognizing a guitar chord is more difficult for the human auditory sense, especially for those new to the guitar chord.

One solution could be to tackle the problem is by way of computerization, the use of computers as a tool recognition system chords on the guitar. Computer characters are consistent on every execution order, the system enables users to get the guitar chord recognition accuracy.

Previous research by Tito Galit Permana, guitar chords for identification using algorithms Harmonic Product Spectrum, get the accuracy rate of 75.68% [1]. In the study conducted by Ardi Priagung, klasisfikasi genre in tune with Naive Bayes method obtained accuracy rate of 83.3%. [2]. Naive Bayesian method is a simple probabilistic classification method that computes a set of probabilities by summing the frequency and the combined value of a given dataset.

Based on this required further research on classifying the guitar chords to increase accuracy by using a different method. This study uses MFCC (Mel Frequency cepstral coefficient) for the extraction of voice and Naive Bayesian classification. MFCC method is a feature extraction technique that has been widely used in voice signal processing, especially on the introduction of the speaker. MFCC methods have specific characteristics to be extracted from the input voice signal which will be recognized. Mel Frequency Ceptral Coefficient (MFCC) is one of the most successful feature extraction in speech recognition. In the study conducted by Eko Riyanto and Sutejo, comparison of voice MFCC feature extraction method, PS-ZCPA,

Of problems and solutions that have been described, this study will classify chord guitar based sound by applying MFCC for the extraction process sound and methods Naive Bayesian for the classification process sound, the expected method of MFCC and Naïve Bayesian can classify chord guitar based on the extraction of sound and measure the level of the accuracy of classification.

1.1 Guitar Tones

Chord or chord progression can generally be defined as a series of tones that are arranged regularly on a scales and scales representing the bias [11] If interpreted in a guitar chord is two or more tones are sounded simultaneously in one excerpt and in one the same time. In a song, chord serves as musical accompaniment or rhythm.

In general, the chord divided into 3 groups: major chords, minor chords and chord substitutions [10].

a. Major chord

Major chord is some major diatonic tones are sounded simultaneously, in the same time. Major diatonic tones are the tones with tone spacing sequence 1-1-1 / 2-1-1-1-1 / 2.

b. Minor chord

Minor chord is some minor diatonic tones are sounded simultaneously, in the same time. Mimor diatonic tones are the tones with the order of the distance between the tone of 1-1 / 2-1-1-1 / 2-1-1.

c. chord substitution

Chord substitution is not derived from diatonic scales major or minor, but more to the interval or distance, composed tone.

Basic guitar chord can be seen in the following figure:

Chord dasar	Mayor	Minor
C	CM	Cm
C#	C#M	C#m
D	DM	Dm
D#	D#M	D#m
E	EM	Em
F	FM	Fm
F#	F#M	F#m
G	GM	Gm
G#	G#M	G#m
A	AM	Am
A#	A#M	A#m
B	BM	Bm

Figure 1 Basic guitar chord

1.2 Artificial Intelligence

Artificial intelligence (Artificial Intelligence) is a branch of science dealing with the use of machines to solve complex problems in a more humane way. This is usually done by following characteristics and analogy think of human intelligence, and deploy them as recognized by the computer algorithm.

The rapid development of technology led to the development and expansion of the scope that requires the presence of artificial intelligence. Smart characteristics have started to be required in a variety of disciplines and technologies. Artificial Intelligence is not only served in various other disciplines. Sliced between psychology and artificial intelligence gave birth to an area known as cognition and psycolinguistics. Sliced between electrical engineering and artificial intelligence gave birth to the various sciences such as image processing, control theory, pattern recognition and robotics.

Artificial intelligence is used to analyze the image of the scenery in the calculation of the symbols that represent the content of the scene after the image is processed to obtain a characteristic. Artificial intelligence can be seen as an integrated three-unity of perception, understanding and action. Perception translate real-world signals in the images become symbols of a more simple, understanding manipulating these symbols to facilitate extracting certain information, and action to translate the symbols that have been manipulated into another signal that can be the end result.

1.3 Voice Processing

Voice recognition is one effort that can be identified or identifiable sound that can be utilized. Voice recognition can be divided into three types of approaches, namely acoustic-phonetic (the acoustic-phonetic approach), an artificial intelligence approach (the artificial intelligence approach), and pattern recognition approach (the pattern recognition approach).

Here is an explanation of each of the blocks:

1. Extracting characteristic.

Is the process of getting a series of scale on the part of the input signal to establish a pattern of learning or test pattern. At the sound signal, the characteristics of the amount is usually the output of some form of spectral analysis techniques such as a filter bank analyzer, LPC or DFT (Discrete Fourier Transform).

2. Learning Patterns

One or more learning patterns related to the voice of the same class, is used to create a pattern representative of the characteristics of the class. The result is commonly called the reference pattern, can be a model that has the characteristic form of statistical characteristics of the reference pattern.

3. Comparison with Model Patterns

Test pattern to be recognized, compared with the reference pattern of each class. The similarity between the magnitude of the test pattern with each reference pattern will be calculated.

4. Decision Logic

Determining class reference patterns which are the most suitable for the test pattern based on the classification of the pattern.

Voice recognition can be generally divided into three stages: feature extraction, modeling and recognition. Feature extraction is an attempt to obtain the characteristics of the sound signal.

1.4 Preprocessing

Preprocessing is to facilitate the process of generating value from the feature extraction. At this stage the sound signal to be processed is analog, so that if processing is done digitally, the voice signal must be converted into a digital signal, in the form of a sequence of numbers with a precision level of certain so-called analog to digital conversion using the analog-to-digital converter (ADC).

1.5 Data Acquisition

The voice that will be used in this study comes from the sound 24 basic guitar chords that are played by plucked simultaneously from top to bottom, and then recorded. The sound of the chord transition 2 of 24 chords will be repeated 15 times recording To get

a result there is less noise recording, the recording is done in a quiet room. Voice data retrieval is done by recording the second voice guitar chords, each one chord to another chord as much as 15 times, so each chord has 10 training data and test data 5.

1.6 Method of MFCC (Mel Frequency cepstral coefficient))

MFCC (Mel Frequency cepstral Coefficients) is one method that is widely used in the field of speech technology, both the speaker recognition and speech recognition. This method is used to perform feature extraction, a process that converts voice signals into multiple parameters [2].

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There is also the signal processing at the MFCC feature extraction using:

1. Pre-emphasis

Pre-emphasisis one type of filter that is often used before a signal is processed further. This filter maintains high frequencies in the spectrum, which is generally eliminated during the process of sound production. The purpose of this filter preemphasis is:
1. decrease noise ratio on the signal, so it can improve the quality of the signal.
2. To obtain the spectral shape of the speech signal frequencies are more subtle.
3. Balancing spectrum of the sound signal.

At the time of producing a sound signal, the human glottis generates about -12 dB octave slope. But when the acoustic energy is released through the lips, an increase of +6 dB. So that the signals recorded bymicrophoneis approximately -6 dB octave slope. Where the spectral shape of a relatively high value for low-lying areas and tends to drop sharply to fekuensi area above 2000 Hz. Preemphasis filter based on the relationship of input / output in the time domain which is expressed in the following equation:

$y(n) = s(n) - \alpha s(n-1)$ (1)

Where:
y (n) = signal preemphasis results
s (n) = signal before preemphasis
α is a constant preemphasis filter, usually worth 0.97.

2. frame blocking

frame Blockingis the division of sound into a number of frames that will be able to facilitate the calculation and analysis of voice, one frame is made up of several samples depending on every how many seconds the sound will be sampled and how large the sampling frequency [7]. The length of the frame is used, greatly affect the success in spectral analysis. On one hand, the size of the frame should be as long as possible to be able to show a good frequency resolution. But on the other hand, the frame size should also be short enough to be able to show a good time resolution. Refresentasi frame blocking function as follows:

x (n) = y (M + n) (2)
Where,
x (n) = Signal after in frame blocking
y = Signal results pre-emphasis
M = overlapping frames
n = 1,2,3, ...

3. windowing

Sound that cut into several frames create voice data into discontinue this resulted in a process of data errors Fourier transform.To avoid data errors in the process of the Fourier transform voice samples which have been divided into several frames need to be a continuous sound by multiplying each frame with a particular window [3]. The type of window that is used in this process is a hamming window. Here is a representation of window functions to the input voice signal.

(N) = x (n) w (n) (3)

Hamming window as the following formula:

w [n] = 0:54 to 0:46 * cos (2 * π * n / (N-1)) (4)

Where:
n = 1,2,3, ...
π = 3:14
N = length of the frame

Window function is most often used in applications voice recognition is a Hamming Window. Hamming window functions produce sidelobe level is not too high (less than -43 dB), in addition to the noise generated is not too large (approximately 1:36 BINS).

4. Fast Fourier Transform (FFT)

Fast Fourier Transform a DFT with a more optimal algorithm, resulting in a faster calculation. With DFT, takes O (n2) to process the data sample as much as nbuah. This will take a long time when more and more data samples. The process of the method of fast Fourier transform (FFT) is to convert each frame of N samples from the time domain into the frequency domain, Fourier transformation is an efficient method for discrete Fourier transformation which is widely used in digital signal processing [5].

FFT method can be done in the time domain and frequency are referred to as desimasi - in - time (decimation-in-time) and desimasi-frequency (decimation-in-frequency). In principle, this algorithm is to break the N-point into two (N / 2)-point, then broke again at every (N / 2) - point to two (N / 4)-point, and so on until there is only one point.

5. Discrete Cosine Transform (DCT)

This stage results do mel-frequency conversion to the time domain using the Discrete Cosine Transform (DCT). Here is the equation used in the DCT.

$$C_j = \sum_{i=0}^{M} X_i \cos\left(j(i-1)2\left(\frac{\pi}{M}\right)\right) \quad (5)$$

Information :
Cj = coefficient C j
j = number of cepstral coefficients
i = number of wrapping
Xi = results of mel-frequency in the frequency of the i-th

1.7 Naïve Bayesian Classification

Naïve Bayesian classification is a simplest method using the existing opportunities, where it is assumed that every variable X is free (independence) [4]. Because the assumptions are not mutually dependent variable, then obtained:

$$P(X \mid Y = y) = \prod_{i=1}^{q} P(X_i \mid Y = y) \quad (6)$$

There are several steps in the classification using Naive Bayesian method, the following steps - steps:

training:

1. Calculate the average (mean) of each feature in the training dataset.
   $$\mu = \frac{\sum x_i}{n} \quad (7)$$
   Where:
   μ = Mean MFCC dataset
   n = The number of data
   $\sum x_i$ = The number of data values

2. Then calculate the variance of the training dataset as on.
   $$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2 \quad (8)$$
   Where:
   σ^2= variance
   μ = mean
   x_i = The value of the data
   n = the number of data

testing:

1. Calculate the probability (Prior) of each class there is a way to calculate the amount of data each class divided by the total number of overall data.
2. Next calculate the probability density. Expressing the relative probability density function. Data with mean μ and standard deviation σ, the probability density function is:
   $$(9)\ \varphi_{\mu\sigma}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$
   Where :
   x = Data input
   π = 3.14
   σ = standard deviation
   μ = mean
3. Having obtained the probability density values, then calculate the posterior of each class using the equation.
   $$posterior = \frac{prior\ x\ likehood}{evidence}$$
   Or it could be written
   $$Posterior = \frac{P(C_i)x\ P(X1\ \ldots\ldots\ldots\ldots\ldots\ldots Xn|C_i)}{P(X1\ \ldots\ldots\ldots\ldots\ldots\ldots Xn|C_i)}$$
4. Having obtained the posterior value of each class, the class corresponding to the input data is the class that has the greatest posterior value.

1.8 Testing Confusion Matrix

Tests conducted on the classification method contained in the accuracy of the classification results. The accuracy of a classification effect on the performance of a method of classification. To perform the test accuracy can be used confusion matrix is a matrix of predictions will be compared with the original class of the input data. Each column of the matrix corresponding to the result of the classification and each line at the inlet. The accuracy of a classification where i = j describes the accuracy of the classification in each class [9]. Here's an exampleConfusion Matrix can be seen in Table 2.

Table 1 Confusion Matrix

Class		Classification Results	
		0	1
Target	0	00	01
	1	10	11

Used to calculate the accuracy of the formula:
$$\frac{jumlah\ akurasi}{total\ data} X\ 100\% = Akurasi\%$$

2. RESEARCH

2.1 Analysis of the Problem

The guitar is a musical instrument of modern popular and widely used as a filling instrument rhythm and melody in a song. Chord or chord knowledge necessary to play the guitar. Akor is a series of tones that build on the harmonization of music [9]. Recognizing a guitar chord is more difficult for the human auditory sense, especially for those new to the guitar chord.

One solution could be to tackle the problem is by way of computerization, the use of computers as a tool recognition system chords on the guitar. Computer characters are consistent on every execution command is given, the system enables users to get the guitar chord recognition accuracy.

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2.2 Analysis System

Systems analysis in this study will explain processes that exist in the basic tone guitar classification system by using the guitar as an input medium. Here is the process flow system to be built can be seen in Figure 2:

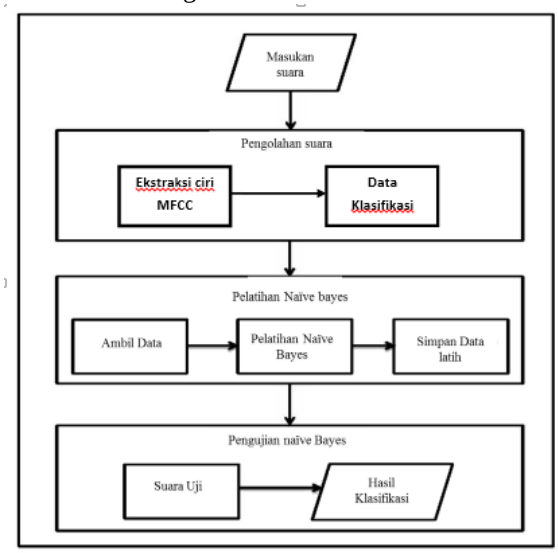


Figure 2, Flow Analysis System

2.3 DC Removal

Here is the equation to calculate the DC Removal.

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

DC Removal Sample calculation for a C chord with a sample of the data signal in the following figure.

Calculate DC Removal:

$$\frac{(-7) + \text{---} + (64)}{24}$$

= 7.5
After the average value is known, subtract the initial signal values with results
DC Removal so the value of the signal becomes:
n0 = -7 - 7.5 = -14.5

count for the next signal data in the same way, after the DC Removal process is

Table 2 DC Data Removal

i	Signal ke i
0	-14.5
1	-11.5
2	-10.5
3	-5.5
4	0.5
5	4.5
6	6.5
7	3.5
8	-3.5
9	3.5
10	-13.5
11	-12.5
12	-16.5
13	-22.5
14	-22.5
15	-1.5
16	2.5
17	-27.5
18	-31.5
19	-9.5
20	26.5
21	50.5
22	58.5
23	56.5

2.4 Pre- emphasize

The equation for Pre-emphasize the process is as follows.

$$y\,[n] = s\,[n] - \alpha\, s[n-1]$$

Information :
Y [N] = signal Pre-emphasize results filter
S [N] = signal before Pre- emphasize Filter
α = 0.97
Samples signal:
Y0 = -14.5
Y1 = (-10.5) - (- 14.5 * 0.97) = 3,565
Here are the Pre-emphasize datahasil

Table 3 Data Pre-emphasize

i	Pre-emphasize ke i
0	-14.5
1	-3.565
2	-2.865
3	4.685
4	-9.685
5	4.015
6	2.135
7	-2.805
8	-6.895
9	6.895
10	-10.105
11	0.595
12	-0.375
13	-10.375
14	-10.375
15	20.325
16	3.955
17	-26.045
18	-4.825
19	21.055
20	35.715
21	24.795
22	9.515
23	-0.245

2.5 Frame Blocking

Here is the equation to make the process of Blocking Frame.

((IN) / M) +1

Information :
I = sample rate
N = sample point (sample rate * time framing (S))
M = N / 2
With time = 50 ms, and sample rate = 16,000 Hz, then obtained Frame size (N)
N = 16,000 * 0.05 = 800 Sample Point
And M = 400
So that the amount of Frame:
= ((16.000-800) / 400)) + 1 = 39

2.6 Windowing

Here is the equation used in the windowing process.

$$w(n) = 0{,}54 - 0{,}46\cos(\frac{2\pi n}{N-1})$$

Information:
N = number of samples in each frame
to-n = index ...
w = value of hamming window n-th
x = the value of the sample signal windowing results

By using the formula obtained the following results:$w(n) = 0{,}54 - 0.46\ cos\ \frac{2\pi n}{N-1}$
Wo = 0:54 to 0:46 cos $\left(\frac{2*3.14*0}{800-1}\right)$= 0:08
thus:

Xo = -14.5 * 0.08 = -1.16
Windowing the results can be seen in Table 4 below.

Table 4 Data Windowing

i	Windowing ke i
0	-1.16
1	-0.2658
2	-0.2852
3	0.3748
4	-0.7748
5	0.3212
6	0.1708
7	-0.2244
8	-0.5516
9	0.5516
10	-0.08084
11	0.0476
12	-0.03
13	-0.83
14	-0.83
15	1.626
16	0.3164
17	-2.0836
18	-0.386
19	1.6844
20	2.8572
21	1.9836
22	0.7612
23	-0.0122

2.7 Fast Fourier Transform (FFT)

Here is the equation for implementing the FFT process Fouries Discrete Transform (DCT).

$$F_{[k]} = \sum_{n=1}^{N} f(n)\cos\left(\frac{2\pi nkT}{N}\right) - j\sum_{n=1}^{N} f(n)\sin(\frac{2\pi nkT}{N})$$

Information :
f (n) = a sound signal
N = number of samples
F [k] = result of FFT
For F0, the obtained calculated as follows:

$$(f_0) = \frac{1}{24}\left[-1.16\left(cos\left(\frac{2\pi * 0 * 0}{24}\right)\right)\right] - j\ sin\ \frac{2\pi * 0 * 0}{24} +$$

$$\left[-0.2852\left(cos\left(\frac{2\pi*0*1}{24}\right)\right)\right] - j\ sin\ \frac{2\pi*0*1}{24} +$$

$$\ldots + \left[0.0122\left(cos\left(\frac{2\pi*0*23}{24}\right)\right)\right] - j\ sin\ \frac{2\pi*0*23}{24} = 0.0248$$

Then F0 = 0.0248
In the same way do the calculations more signal data. So that would be obtained from the data signal FFT results can be seen in Table 5 below.

Table 5 Data FFT

i	FFT ke i
0	0.0248
1	-0.0032
2	0.0045
3	0.0058
4	0.0061
5	-0.0033
6	0.0052
7	0.0078
8	0.0064
9	-0.0061
10	0.0052
11	-0.0048
12	0.0033
13	-0.0045
14	-1.0727
15	1.4171
16	-1.6654
17	2.3508
18	-0.3434
19	0.9688
20	7.5436
21	6.8763
22	6.5985
23	4.7714

2.8 Mel frequency warping

Here is the formula to make the process of Mel Frequency Warping.

$$Y[i] = \sum_{j=1}^{N} S[j]H_i[j]$$

Information:
N = the number of magnitude spectrum
S [j] = magnitude of the frequency spectrum
Hij = coefficient filterbank at frequency j ($1 \leq i \leq M$)
M = number of Channel filterbank
To get Hi used the formula:

$$H_i = \frac{2595 * \log(1 + \frac{f}{700})}{\frac{Si}{2}}$$

Is known :
S0 = 0.0248

$$H_0 = \frac{2595 * \log(1 + \frac{16000}{700})}{\frac{0.0248}{2}} = 228299.9769$$

The importance of the S0 = 0.0248 * 228299.9769 = 7149.8394
In the same way the signal obtained filterbank results can be seen in table 6 below.

Table 6 Data Filterbank

i	Filterbank ke i
0	7149.8394
1	6712.7077
2	6018.2896
3	5722.30822
4	6018.2896
5	5454.0750
6	6018.2896
7	5722.30822
8	6712.7077
9	7272.1003
10	7756.9067
11	10577.6006
12	10908.1506
13	7756.9067
14	7272.1003
15	6712.7077
16	38784.5335
17	13425.4154
18	174530.5003
19	34906.0801
20	5454.0750
21	10577.6004
22	10908.1506
23	7933.2006

2.9 Discrete Cosine Transform (DCT)

DCT is the final step of the primary process MFCC feature extraction. The basic concept of the DCT is mendekorelasikan mel spectrum so as to produce a good representation of local spectral properties.

Here is the formula used to calculate the DCT.

$$\tau_n = \sum_{k=1}^{K} (\log S_k) \cos[n\left(k - \frac{1}{2}\right)\frac{\pi}{K}]$$

Information:
Sk = output of the filterbank at index k
K = number of coefficients expected
Koef (k) = 24
For n = o then,

$$n_0 = \log(7149.8394) \cos\left[0\left(0 - \frac{1}{2}\right)\frac{3,14}{24}\right] + \log(6712.7077) \cos\left[0\left(1 - \frac{1}{2}\right)\frac{3.14}{24}\right] + \cdots + \log(7933.2006) \cos\left[0\left(24 - \frac{1}{2}\right)\frac{3.14}{24}\right]$$

= 17.4437
So no = 17.4437

Likewise with other data after the calculation, then the signal DCT result can be seen in Table 7 below.

Table 7 Data DCT

i	DCT ke i
0	17.4437
1	17.41414
2	17.38534
3	17.3572
4	17.32965
5	16.67375
6	16.64597
7	16.59144
8	17.10545
9	17.03262
10	17.00841
11	16.95997
12	16.9842
13	16.91138
14	16.76407
15	16.7888
16	16.71437
17	16.68942
18	16.66441
19	16.88701
20	16.83805
21	16.76407
22	16.81347
23	16.68942

2.10 Naive Bayesian Analysis Training Process

Naive Bayesian training is done to obtain the mean and variance. Here's an explanation of the naive Bayesian training process:

2.11 Train Data

Train Data is the stage for the training data using naive Bayesian method. Of the characteristic features listed in Table 3.10 would then calculated the mean and variance of each class, the mean and the variance will be used to search probabillitas likelihood, with a density formula. The mean value can be calculated using equation 2.8 and the value of the variance can be calculated using the equation:

$$\mu = \frac{\sum x_i}{n}$$

Where:
μ = mean
n = The number of data
$\sum x_i$ = The number of data values

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2$$

Where:
σ^2= variance
μ = mean
x_i = The value of the data
n = the number of data
Following the calculation of the mean and variance based on a feature MFCC in Table 3.10:

Guitar Tone G

$$\mu\ FFT\ \text{Nada G} = \frac{0{,}70463 + 0{,}68916}{2}$$

= 0.69690

$$\sigma^2\ FFT\ \text{Nada G} = \frac{1}{2-1}.(0{,}70463 - 0{,}69690)^2 + (0{,}68916 - 0{,}69690)^2$$

= 0.00012
A guitar tone

$$\mu\ FFT\ \text{Nada A} = \frac{0{,}66979 + 0{,}64519}{2}$$

= 0.65749

$$\sigma^2\ FFT\ \text{Nada A} = \frac{1}{2-1}.(0{,}66979 - 0{,}65749)^2 + (0{,}64519 - 0{,}65749)^2$$

= 0.00030

table 8 Mean and Varian notes G and A

Nada	Nilai	Fitur		
		FFT	MEL FILTER	DCT
G	Mean	0.69690	4.33926	39.39922
	Varian	0.00012	0.00731	0.41231
A	Mean	0.65749	5.55330	40.79819
	Varian	0.00030	0.26281	1.16603

2.12 Save Data Practice

Store data is the stage to keep the mean and variance of the training data into txt form.

2.13 Naive Bayesian Analysis Testing Process

Testing is done to classify the guitar chords are included with the data already trained, so that can know the results of the classification.

2.14 Tone Test

Test tone is the tone that will go through the testing phase of training data, previously performed the same stage with the training pitch to get the value of Feature Feature. Examples of the tone to be tested can be seen in Table 9.

table 9 Sample Test Tone

features	Value
FFT	0.68916
MEL FILTER	4.27881
DCT	38.94517

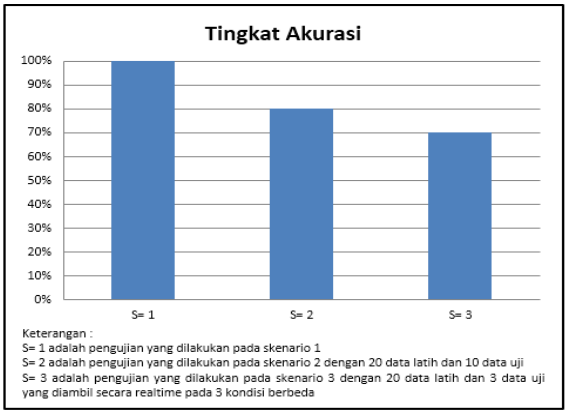
Posterior Nada G
Posterior = P (Tone G). P (FFT | Nada G). P (MEL | Nada G). P (DCT |
Tone G). / Evidence
Posterior = (0.5 * 28.41000 * 3.63556 * 0.48399) / 25.00132
Posterior = 24.99476 / 25.00132
Posterior = 0.99973
Posterior Tone A
Posterior = P (Tone A). P (FFT | Nada A). P (MEL | Nada A). P (DCT |
Nada A). / Evidence
Posterior = (0.5 * 4.37323 * 0.03541 * 0.08477) / 25.00132
Posterior = 0.00656 / 25.00132
Posterior = 0.00026
Posterior (Tone G)> posterior (Tone A) It so right class for test data is Nada G.

3. COVER

3.1 Testing and Results

Testing method aims to determine the outcome of the MFCC and Naive Bayesian methods in classifying a guitar chord. In this study, plan testing is done with a few scenarios. Here is a scenario that will be done.

1. Guitar chord tone test that has been used as training data.
2. Guitar chord tone test that has not been previously trained and tested the effect of the amount of training data on the level of accuracy.



Based on the testing that was done and the MFCC method naïve Bayesian methods can be used to classify the basic tone of the guitar. and based on the above test concluded that the consistency of training data which affect the level of accuracy when testing using different instruments resulting accuracy is likely to change.

3.2 Conclusion

The results of the research that has been done in the preparation of this paper as well as referring to the purpose of research, it can be concluded.

1. MFCC and Naive Bayesian methods can be used to classify the basic tone of the guitar based sound.
2. This level of accuracy MFCC and Naive Bayesian methods in classifying the basic tone of the guitar based sound is 70%.

3.3 Suggestions

Based on the results of research that has been reached at this time, there are some suggestions that may be useful if there are going to conduct similar research, namely:

1. Dataset tone used should have the same quality.
2. To obtain a high level of accuracy in classifying the various chords, you should use a good quality instrument.

BIBLIOGRAPHY

[1] Tito Galit Permana, Dr. Ir. Bambang Hidayat, and Eko Susatio ST, MT, 2013. *Guitar Chord Identification Algorithm Using Harmonic Product Spectrum.* Thesis. Faculty of Electrical and Communication University of Telkom.

[2] Ardi Priagung, Siti Kurniawati F. Hendri A., I Dwi Gede A., and Oscar Sampars T., 2014, *On the Tracks By Genre Classification Naive Bayesian method* .Skripsi. Brawijaya University, Malang.

[3] Eko Riyanto, Sutejo, 2014, *Voice Feature Extraction Methods Comparison MFCC, ZCPA AND LPC*. Essay. STMIK HIMSYA.

[4] Setiawan, A., Hand, PK 2012. *Gender Based Voice clustering with Time Domain-Based Feature Extraction* .Volume 3, # 5, January 2012.

[5] Sijabat, DW, 2009. *Simulation-Based Isolated Chord Recognition Speaker Dependent Method with Hidden Markov Model*. Skripsi.Universitas Indonesia.

[6 Anna Dara Andriana, 2013, *Software To Unlock Application On Computer With Voice Commands Using Mel Frequency Cepstrum Coefficient Method*. Volume 2, No.1, March 2013.

[7] Huda, M., Basuki, DK, Akbar, F., Permana, FJ 2011. *Tone-Tone Conversion Acoustic Being Chord Using Pitch Class Profile*. Skripsi.Institut Technology Ten November.

[8] Wisnudisastra E. 2009. *Introduction to Musical Instruments Guitar Chord On Using the codebook with MFCC Feature Extraction Techniques*. Essay. Bogor Agricultural Institute.

[9] Maulana, MA 2013. *Implementation of Speech Recognition on Toddler Card Games for Android-Based Childhood Toddler*. Essay. University of Northern Sumatra.