International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 06 | June 2022 www.irjet.net p-ISSN: 2395-0072

Prediction Model for Emotion Recognition Using EEG

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Abstract: **EEG signal-based emotion recognition has been employed in medical, affective computing, and other biotech domains. Compare the work by analysing the main factors involved in the recognition process, such as feature extraction, subjects, and classifiers. The emotional activation curve is used for the demonstration of the emotional activation process. Have used different algorithms, each of which extracts features from EEG signals and classifies emotions using machine learning techniques such as CNN, KNN, LSTM, and random forest, in which different parts of the trail are used to train the proposed model and predict its impact on emotion recognition results.**

This paper gives a comparative analysis of existing approaches and proposed methods. The accuracy of identifying depression patients' emotions as positive, negative, or neutral is better when a random forest method is applied.

Keywords: *Random Forest, CNN, KNN and LSTM, EEG, Mind Monitor*

I. Introduction

Emotion and voice recognition can be used to identify depression, which is a prevalent mood disorder defined as feelings of melancholy or anger that interfere with a person's personality and can be used to determine and classify people's depression. As a result, the earlier depression is identified, the more easily it can be treated.

EEG (electroencephalography) is being used in brain systems and rehabilitation engineering to address this problem with a low-cost, non-invasive, and high-resolution technology.

The experimental paradigm, emotion and voice feature extraction, feature selection, training, and testing datasets, as well as geographical information feature extraction and selection, are all covered in this work.

The main focus will be on investigating different categorization strategies and how they affect accuracy and module selection, as well as which model is best and how to select the best module.

Developed an online web application that may be used to determine whether a person is depressed on a positive, negative, or neutral scale.

The participants were given stimuli of six human faces presented with faces in the crowd, and the dataset included 16 patients with depression and 14 healthy controls.

Dimension features can deceive classifiers, so selecting the correct features is crucial. Support vector machine, Bayes Net, K-nearest neighbor (knn), Convolutional neural network (CNN), Long short-term memory (LSTM), and Random Forest approaches are widely used for discriminating classes.

EEG signals, like many other physiological signals, are nonlinear and nonstationary. To analyse them, linear and nonlinear parameters such as spectrum density, Lempel complexity, variance, fluctuations, entropy, correlation dimension, and permutation entropy are used.

electroencephalogram (EEG) system and device with 1/4/812/24/36/48/60 channels. It is the process of recording and interpreting electrical activity in the brain. The electrical impulses produced by brain nerve cells follow a rhythmic pattern.

This is consistent with the neuroscience premise that neurons are the brain's building blocks. These neurons transmit data from the rest of our body to the brain and back. It analyses the change in electrical potential caused by an electrically active cell's impulse. Ion flow causes the action potential. Ions are positively or negatively charged molecules. A neuron can generate a current by modifying the flow of these ions, resulting in an action potential. If neurons stimulate the ion flow from one neuron, these flows accumulate, and a threshold is met, indicating that this neuron will create an action potential. EEG recordings are now available.

EEG equipment is primarily used to capture and measure brain-wave patterns, and the resulting recording is referred to as an electroencephalogram or EEG.

For the EEG dataset, eight linear features and nine non-linear features were derived from alpha 8-––13Hz, beta 13-30Hz, and theta 4-8Hz waves, with the beta frequency band receiving the greatest accuracy using Random Forest and KNN.

The channel dimension comprises EEG spatial information since the electrode channels are positioned at different locations on the human skull. The best spatial information must be chosen while selecting EEG channels. The common spatial pattern (CSP) was demonstrated to be the most successful technique for brain interface optimization of the spatial spectrum filter in the previous research.

This research compares multiple categorization methods to offer an excellent EEG-based depression diagnosis approach based on geographical information.

II. Implementation:

1. Data Selection and Loading

The data selection process involves choosing data from the EEG emotion dataset to predict depression in patient emotions. We need EEG equipment to collect real-time data. A few questions may arise, so let's address them.

2. Device configuration:

The dry electrodes of the Muse 2 headset are made up of a single metal that functions as a conductor between the electrodes and the skin. The connection is aided by a small amount of sweat between the skin and the electrode. Wet electrodes, which use an electrolytic gel as a conductor between the skin and the electrodes, are also available. The Muse is a dry electrode that is easy to use.

Seven sensors are included in the Muse headband, four of which are passive electrodes.

Frontal electrodes: AF7 and AF8 Temporal electrodes: AF7 and AF8 Frontal electrodes: AF7 and AF8 Temporal electrodes: AF7 and AF8 Temporal electrodes: AF7 and AF8 Temporal electrodes: TP9 and TP10 are two different types of TP.

A reference sensor (Fpz) and two bridging grounds are located in the centre of the forehead.

In terms of brain structure, the 10-20 placement divides the brain into some important areas for EEG implantation.

Executive processes including planning, decision-making, expression, behaviour, and managing certain parts of speech and language are all pre-frontal (Fp) activities.

Movement control, logic, emotions, speaking, and problem-solving are all frontal (F) functions.

Auditory (A), memory (M), and processing (P) are all temporal (T) concepts.

Parietal (P): attentiveness, sensory perception

Visual functions are performed by the occipital (O) cortex.

Sensorimotor activities are located in the central part of the brain (C).

Now that we have this brain structure, we can insert the muse sensors. Figure 4 depicts the 10-20 system, with colours indicating where the Muse2 electrodes should be placed.

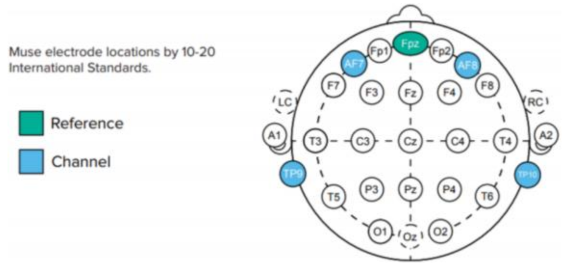

Figure 1: *10-20 system placement of the muse2 electrodes*

Src: Mind Monitor

The reference electrode in Muse is Fpz, and the electrodes are TP9 (left ear), TP10 (right ear), AF7 (left forehead), and AF8 (right forehead). It monitors the potential differences (voltage) between the active electrodes and Fpz rather than capturing brain inputs. Muse measures voltage fluctuations in the temporal/parietal lobe (TP) and frontal lobe (FL) (AF).

As neurons are present in the brain and are wired together, this is how it functions. Neurons frequently fire in clusters, and a larger cluster of neurons firing at the same time results in a larger amplitude in our EEG readings. According to a study, huge groups of neurons fire together every now and then, while small groups fire more frequently. As a result, lower frequency brain waves had higher amplitude and vice versa.

Let's take a look at what human brain waves are and how they can aid in data collection.

Based on the logarithm of the power spectral density (PSD) of the EEG data for each channel. The EEG PSD values read from the sensors are typically in the -1 +1 range. These have the following frequency spectrum:

Delta - 1-4Hz

Theta - 4-8Hz

Alpha - 7.5-13Hz

Beta - 13-30Hz

Gamma - 30-44

3. **Collecting the data**

The Mind Monitor app is a popular data collection app. This is a third-party app that assists in the data collection from Muse devices.

Sprinkle some water on the electrodes on the Muse device for better measurement; this will assist in leaving a trail of sweat on the forehead, which will improve the connection.

Also, set the notch filter to the desired notch frequency, which eliminates electrical signals from the power line. You can enable marker buttons just above the notch frequency. These can be used to identify certain areas of our data. This will aid in the labelling of specific activities during the recording process.

To record, press the record button on Muse, which will create a CSV file. By default, data for absolute brain waves, raw EEG signals, accelerometer, gyroscope, headband on or off, and HSI is captured every second (Horseshoe Indicator).

The recording interval can be modified, and it can be set to constant, i.e., raw EEG signals are captured at 256 Hz, and brain wave data is acquired at 10 Hz.

We can band-pass the signal after getting the EEG data to keep the frequencies that carry relevant information and apply a notch to eliminate AC inference. Now, distinct frequency bands are analysed independently by band pass filtering each band, namely delta, theta, alpha, beta, and gamma, which have lower frequencies with higher amplitude and vice versa. Following that, we can segment the data using markers to distinguish sentences; these segments are then used as independent training/classification trails.

We can employ Short Term Energy (STE) for feature extraction, which is similar to multiple speech processing methodologies. Equation 1 is used to determine the STE.

$$Em = \sum [x(n)w(m-n)]^2$$

The length of the hamming window function for the samples is 'w,' and the input EEG signal is 'x.'

The multi-taper (MT) spectrogram can be used for visualisation to validate the method of removing delta band influence from the beta band in EEG signals. The multi-taper method multiplies the signal with pairwise orthogonal data taper windows to provide multiple independent estimates from the same sample.

After that, you can get the final spectrum by averaging all statistically independent tapered spectra. We now need the time domain in order to specify the taper parameters for the time-bandwidth product and the number of tapers, as well as the moving window length with sample shift. The MT spectrogram of the beta-delta band signal can be captured with the STE for syllable-like spectral features.

Now we know how to collect the data from the EEG (MUse2 device) and which to select.

Here how the dataset looks like:

Table 1: *Sample Muse2 EEG dataset.*

mean_0_a	mean_1_a	mean_2_a	mean_3_a	mean_4_a
4.62E+00	3.03E+01	########	1.56E+01	2.63E+01
2.88E+01	3.31E+01	3.20E+01	2.58E+01	2.28E+01
8.90E+00	2.94E+01	########	1.67E+01	2.37E+01
1.49E+01	3.16E+01	########	1.98E+01	2.43E+01
2.83E+01	3.13E+01	4.52E+01	2.73E+01	2.45E+01
3.10E+01	3.09E+01	2.96E+01	2.85E+01	2.40E+01
1.08E+01	2.10E+01	4.47E+01	4.87E+00	2.81E+01

The data set contains three label counts namely positive negative and neutral

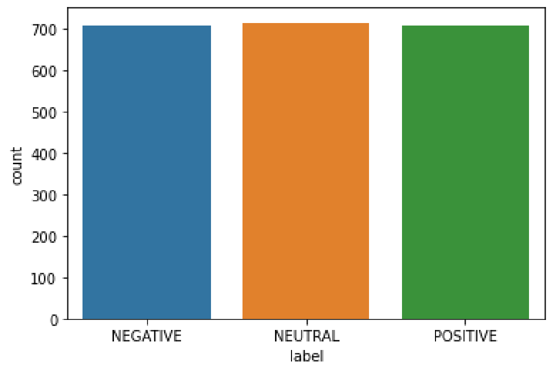

Figure 2: *Dataset label count positive:708, negative:708, neutral:716*

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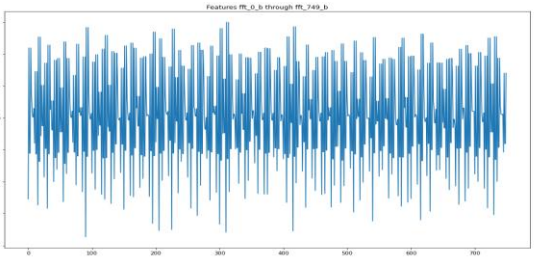

Figure 3: *Dataset FFT signal*

4. **Data Pre-processing**

Data preprocessing is the process of removing the unwanted data from the dataset, i.e.

- Removing missing data: The null values are removed.
- Encoding Categorical Data: they are variable with a finite set of label values.
- MIN-MAX scalar: it scales all the data features in the range [0,1] or in the range [-1,1] if any negative values in the dataset. Scalar transforms features by scaling each feature to a given range.
- Data Normalisation: Use to scale the data of an attribute so that it falls in a smaller range, such as -1.0 to 1.0 or 0.0 to 1-.0.
- Batch Normalisation: Applied on neural networks where training is done in mini-batches on neuron activation such that the mean of output lies close to 0 and the standard deviation lies close to 1.
- Layer Normalisation: dependent on batches, then the normalization is applied to the neuron for a single instance to all features. Here, mean activation and standard deviation remain close to 0 and 1.

The adjustments made to our data before applying the method are referred to as pre-processing. It's used to turn unclean data into clean data.

The data must be in the appropriate format for the machine learning model to get the best results.

Outlier detection, removal, and missing values are the initial steps in the preprocessing pipeline. Here, we employed a distribution-based outlier detection approach, in which a combination of distributions is fitted to the data. Because the data in our software would be difficult to fit adequately with just one distribution, we might be able to attain a more accurate fit by using a blend of distributions. As a result, we employ a mixture model. In this example, we utilised three different distributions.

When the distribution is less than 0.005, a data point can be called an outlier. In a dataset with 2000 data points, we use outliers on average approximately ten times, with 30 outliers.

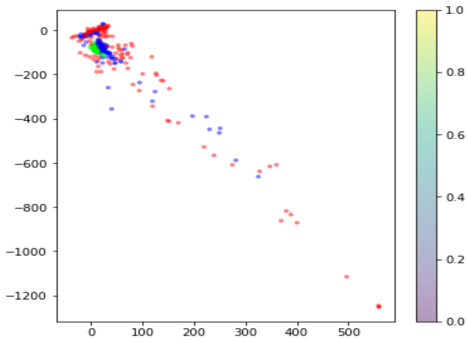

Figure 4: *An outlier detection using a mixture model.*

5. **Data Transformation and Dimension Reduction.**

Dimension reduction with PCA (Principal Component Analysis) is used for feature engineering and data transformation. PCA is used to reduce the dimensions of the data for visualisation, such as plotting a 2D or 3D graph by lowering the dimensions to 2 or 3. Here, we must choose which components should be included in the data. In PCA, the first and last components explain the most and least variance, respectively. Now we select a variance that does not diminish significantly.

For the engineering feature in the windows:

1. Add the frequency with the largest amplitude as an indicator of the most relevant frequency in the window for the engineering characteristic.
2. Multiply each frequency with its amplitude to get the weighted signal average of the frequency.
3. Divide the sum of the results by the sum of the amplitudes.
4. Calculate the spectral entropy of the system. We compute the power spectral density, then normalize the values to the sum of 1, allowing us to see it as a probability density function.
5. Calculate the entropy using the entropy calculation.

The next step is to combine all of our datasets into a single large dataset. We shuffle all of our user data at random and use it as input for our model. This will assist

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us in determining whether or not our situation is non-temporal.

Creating, validating, and testing training and test sets. We'll divide our data by 60-20% into training data, 20% into validation data, and 20% into test data at random.

6. **Machine Learning Models/ Classification**

Using sci-kit-learn, build six distinct machine learning models. Non-deterministic models have a random component, whereas deterministic models always produce the same results.

Deterministic models are:

- Convolutional Neural Networks (CNN)
- K-nearest Neighbours (KNN)
- LSTM (recurrent neural network)

Non-Deterministic models are:

- Neural Network
- Random Forest (RF)

Here we found that the Random Forest Model, with grid search, gives the best accuracy of 97%, followed by CNN, with an accuracy of 82%, and KNN, with 94%.

The reason for utilising the RNN model is that it tries to find out what the differences are between our positive and negative instances so that classification can be performed. These networks, known as RNNs, read your input sequentially while maintaining a "memory" of what they've already read. Because of the association between words, these are extremely beneficial when dealing with text.

It now combines the predictions of several decision trees into a single model, as it does with Random Forest. Also, by integrating several trees into one ensemble model, RM helps reduce the large variance of a flexible model like a decision tree.

The Neural Network will require far more data than a single person can provide. For the sake of performance, the neural network will just shred the interpretability of our features to the point that they become worthless for specific models or tasks.

The outcome of a KNN algorithm is entirely dependent on the nearest neighbours, which may differ depending on our selection. It is also affected by distance metrics.

CNN, on the other hand, takes the characteristics from the input data and extracts them. which are really useful for conducting research.

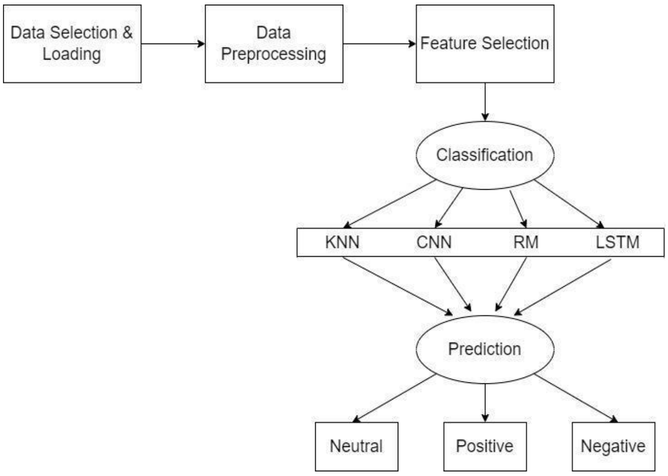


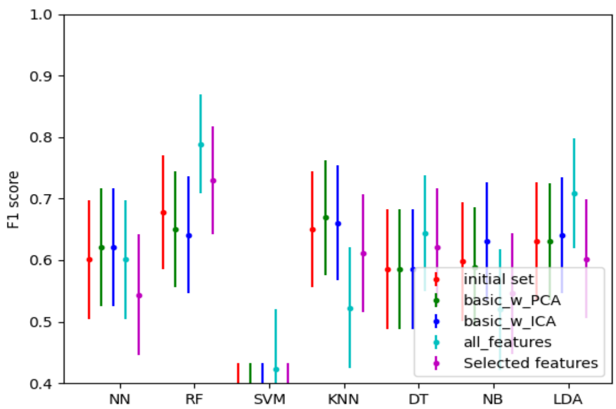
Fig. 4: System FLow diagram

III. Result

Table 2: *Classification Techniques with an Accuracy Difference*

Models ->	KNN	CNN	RM	RNN (LSTM)
Accuracy	94%	86%	97%	95%
MAE	0.07	0.58	0.05	0.4
MSE	0.41	0.75	0.11	0.30
RMSE	0.56	0.86	0.33	0.66

Random Forest has the highest accuracy of 97 percent, followed by CNN and KNN, which have 84 percent and 94 percent of accuracy, respectively.



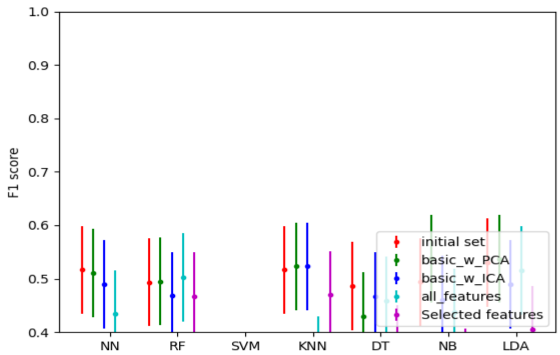


Fig. 6: Evaluation of a three-label classification.

Found that the random forest model, with grid search, gives the best performance: an F1 score of around 0.85.

IV. Conclusion

The system analyses the user's mindset using EEG signals and makes a prediction based on that. Because these solutions are more affordable, government hospitals and medical experts may prefer to use them for diagnosis.

This research looks at a variety of categorization model strategies that can help you get the best results. Random Forest has the highest accuracy of 97 percent, followed by CNN and KNN, which have 84 percent and 94 percent accuracy, respectively.

Acknowledgment

I'm extremely grateful to Dr. Reena Pagare, Assistant Professor, MIT ADT University, Pune, India, who has been an invaluable source of help and direction during this project.

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References

[1] Beomjun Min, Jongin Kim, Hyeong-jun Park, and Boreom Lee "Vowel imagery decoding towards silent speech BCI using extreme learning machine with an electroencephalogram," *BioMes research international,* vol. 2016, 2016.

[2] Katharine Brigham and BVK Vijaya Kumar "Imagined speech classification with EEG signals for silent communication: preliminary investigation into synthetic telepathy," in *Bioinformatics and Biomedical Engineering (iCBBE), 2010 4th International Conference On.* IEEE, 2010, pp. 1-4.

[3] Xuemin Chia, John B Hagedorna, Daniel Schoonovera, and Micheal D'Zmuraa, "EEG-based discrimination of imagined speech phonemes," *International Journal of Bioelectromagnetism,* vol.13, no. 4, pp.201-206, 2011.

[4] Sarah N Abdulkader, Ayman Atia, and Mostafa-Sami M Mostafa, "Brain computer interfacing: Applications and challenges," *Egyptian Informatic Journal,* vol. 16, no. 2, pp. 213-230, 2015.

[5] Bernard J Baars and Nicole M Gage, *Cognition, brain, and consciousness: Introduction to cognitive neuroscience - Chapter 7, 11,* Academic Press, 2010.

[6] Tan Tian Swee, Sheikh Hussain Shaikh Salleh, and Mohd Redzuan Jamaludin, "Speech pitch detection using short-time energy parameters to classify syllables in the spanish language," in *Iberoamerican Congress on Pattern recognition.* Springer, 2005, pp.161-170.

[7] David J Thomson, "Spectrum estimation and harmonic analysis," *Proceeding of the IEEE,* vol. 70, no.9, pp. 1055-1096,1982.

[8] Lija V Bondarko, "The syllable structure of speech and distinctive features of phonemes," *Phonetica,* vol. 20, no. 1, pp.1-40, 1969.

[9] Jacques Mehler, "The role of syllables in speech processing: Infant and adult data," *Phil. Trans. R. Soc. Lond. B,* vol. 295, no. 1077, pp. 333-352, 1981.

[10] Waleed H Abdulla, David Chow, and Gray Sin, "Cross-words reference template for dtw-based speech recognition systems," in *TENCON 2003. Conference on Convergent Technologies for the Asia-Pacific Region.* IEEE, 2003, vol. 4, pp. 1576-1579.

[11] Hiroaki Sakoe, " Two-level dp-matching-a dynamic programming-based pattern matching algorithm for connected word recognition," *IEEE transactions on Acoustics, Speech, and Signal Processing,* vol. 27, no. 6, pp. 588-595.

[12] Katharine Brigham and BVK Vijaya Kumar, " Subject identification from electroencephalogram (EEG) signals during imagined speech," in *Biometrics: Theory Application and systems (BTAS), 2010 Fourth IEEE International Conference on.* IEEE, 2010, pp. 1-8.

[13] Martin Spuler, "A high-speed brain-computer interface (BCI) using dry EEG electrodes," *Plos one,* vol. 1, no. 2, pp.20172400, 2017.

[14] Sergio Machado, Fernanda Araujo, Flavia Paes, Bruna Velasquez, Mario Cunha, Henning Budde, Luis F Basile, Renato Anghinah, Oscar Arias-Carrion, Mauricio Cagy, et al., "EEG-based brain-computer interfaces: an overview of basic concepts and clinical applications in neurorehabilitation," *Review in the Neurosciences,* vol.21, no. 6, pp.451-468, 2010.

[15] Kang Wang, Xueqian Wang, and Gang Li, "Simulation experiment of BCI based imagined speech EEG decoding," *arXivpreprint arXiv:1705.07771,* 2017.

[16] Mel-frequency cepstrum. http:/en.wikipedia.org/wiki/Mel-frequency_cepstrum

[17] Douglas O'Shaughnessy Rivarol Vergin, "Generalised Mel Frequency Cepstral coefficients for Large-Vocabulary Speaker-Independent Continuous Speech Recognition," *IEEE transaction on speech and Audio Processing,* vol. 28, no. 5, pp. 525-532

[18] Abhay Kumar, "Voice Based Control Command Signal Generation for Intelligent System," *In Electrical Computer and Electronics (UPCON), 2015 IEEE UP section conference, Allahabad,* 2015, pp.1-6.

[19] MFCC (Mel Frequency Cepstral Coefficients) for audio format -website; iq.opengenus.org

[20] Marco A. Wiering, Lambert R.B. Schomaker, "Multi-Layer Support Vector Machines" *In book: Regularisation, optimization, Kernels, and Support Vector Machines.* Edition: *CRC Machine Learning and Pattern Recognition Series, Boca Raton, USA, Oct 2014.* Chapter. 20

[21] Support Vector machine (SVMs) versus Multilayer Perception (MLP) in data classification, *in Mathematics Dept., Computer Science Section, Faculty of Science, Sohag University, SOhag, Egypt.,* Egyptian Informatics Journal, Volume 13, Issue 3,November 2012, pages 177-183.

[22] You-xi Wu, Lei Guo, Yan Li, Xue-qin Shen, Wei-li Yan, "Multi-Layer Support Vector Machine and its Application," *In 2016 International Conference on Machine Learning and Cybernetics.* Print ISBN: 1-4244-0061-9; INSPEC Accession no. 9155546, Dalian, China.