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NON-RD_DCNN: A Deep Learning Model for Multi-Chord Music Classification

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ABSTRACT: A chord classification is a conventional category that designates some pieces of music as belonging to a shared tradition or set of conventions. It must be distinguished from musical style and form. There are numerous ways to categorize music into distinct genres. Pop, Hip- Hop, Rock, and Metal are some of the most popular chord genres. Ordering harmony files in view of their kind is a troublesome assignment with regards to music data recovery. Programmed harmony order is fundamental while endeavouring to separate music from a colossal assortment. It has pragmatic applications in an assortment of disciplines, for example, programmed labelling of an obscure piece of music (helpful for applications like Spotify, Wynk, and so on.).In this work, a novel model termed as NON-RD_DCNN is developed in two phases. In the first phase, the NONRD algorithm will be used for improvising the extracted data. The Further comes the second phase, in which the Deep-CNN model is used for predicting the output class label. For implementing the model, the GTZAN dataset as an input, which is the most popular music dataset that has file size of around 1 GB. The NON-RD_DCNN model gives the results like accuracy, loss, val_accuracy, val_loss.

Keywords: Chords, Music, Classification, Deep Learning.

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1. INTRODUCTION:

Chord types are a bunch of distinct terms that give undeniable level data around a couple kinds of music (jazz, old style, rock...). Music order is viewed as a troublesome endeavour because of the choice and extraction of adequate sound components these days, web music data sets are detonating, making it incredibly challenging for purchasers to get to them. The class is one strategy for orchestrating and ordering tunes. Some characteristics of classifications help to recognize them. structure, consonant substance, and instrumentation are terrifically significant parts of music. While unlabelled information is effectively open, music tracks are not. With the right class labels, it's significantly more straightforward to track down the thing you're searching for. The ability to computerize the occupation of perceiving melodic labels takes into account the making of drawing in material for clients, like music revelation and playlist age, as well as music naming and arranging for content suppliers. Fostering this technique needs extricating acoustic attributes that are superb assessors of the class in which we are intrigued, trailed by at least one acoustic element that are great assessors of the class in which we are intrigued. In specific conditions, relapse stage or multi-mark arrangement is utilized. Highlight extraction has generally depended on evidence handling. Front-end for computing helpful attributes from a period or recurrence area sound portrayal. The elements are then utilized as contribution to the AI and profound learning stage [1].

Genre classification is compared with various types of data into a solitary character and gives the life its name. Nowadays music is a fast-growing business that creates new tunes. Several new sounds are created with a sound sign. The sound sign has several highlights [3]. CNN [4] is an extraordinary sort of brain network that has a brace like a geography. This lattice can be straight like time-series information or a 2D brace like that of a picture. CNN utilizes a framework like a multi-facet perceptron that lessens the handling prerequisites [2]. The proposed approach uses the contribution to the AI stage [5].

This work is visiting utilize GTZAN informational collection which is fundamentally renowned in Music Information Retrieval (MIR). The deep learning models are having a major impact for making a sense about the multi class labels and give their best results by improvising the data pre-processing phase.The work will be helpful for future developers to proceed with their research on CNN algorithms.

2. LITERATURE SURVEY

This section mainly focuses on some of the existing works on the music classification. Ghildiyal A et al., [6], The analysts showed a model in view of SVM, Decision Tree, and CNN, which has involved inputs for different models as well as the sound cell-spectrogram, accomplishes 91% exactness, which is comparable to human comprehension of the class with

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the most elevated precision. Nonetheless, the paper has a limit in that the nation and rock sorts were mistaken for different styles.

KG Srinivasa et al., [7] introduced several feature extractors-based classifiers for the classification of Music Genre. The scientists showed algorithms like Logistic Regression (LR) and K-Nearest Neighbors (K-NN) performed sensibly well when contrasted with further developed calculations like Recurrent Neural Networks (RNN) and Support Vector Machines (SVM). The most extreme precision accomplished with Neural Networks was 86%, and the report likewise has a burden in that it didn't assess how well every order framework predicts individual classes. This could be achieved by making a disarray lattice or plotting Receiver Operator Characteristic Curves (ROC).

Bannai H et al., [8] introduced the Similarity-based music kind order to group the capacities. One normal strategy for ordering music is to address each piece of information as an element vector, which is then characterized utilizing ordinary AI calculations. Tracking down great highlights for music characterization, then again, is a troublesome endeavor. Execution worm 15, execution letters in order 16, and alternate ways, for example, 1, 10 letter set positions are models. We want to explore different avenues regarding bigger measures of information, and we evaluate the characterization exactness of emblematic information as well as acoustic information, which is a disadvantage of this paper.

Y Zhuang et al., [9] proposed the music genre classification with transformer classifier in view of music data recovery. An automatic arrangement of music is a huge task in the field of MIR research. Existing approaches undertaken the zeroed in on the arrangement of sorts, feelings, craftsmen, and notes. Ordinarily, ongoing investigations utilized sound, images, verses, and social data in AI calculations to play out these errands. The Chord Classification is a difficult assignment with a variety of uses in the field of programmed arrangement. Previously, many individuals utilized it customarily. This paper has a limit to the issue that we utilize the multi-head self-consideration instrument to independently get familiar with the boundaries for various recurrence areas.

Further developing Music Genre Classification by brief time frame highlight combination [10] by Anders Meng, Peter Ahrendt, and Jan Larsen. In this paper, the issue of music type grouping resolves numerous issues and one of these being the recognizable proof of helpful elements. Some brief time frame highlights have been proposed in the writing, yet a couple of elements have been proposed for longer time scales.

CH Lee et al., [11] proposed the Modulation otherworldly differentiation (MSC) and regulation ghostly valley (MSV) are then registered from each logarithmically-divided adjustment sub band. A data combination approach that coordinates both component level combination and choice level mix is utilized to further develop the characterization precision.

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Tests led on the GTZAN dataset have shown that our proposed approach outflanks different methodologies with a similar trial arrangement. This paper has a restriction to Human arrangement blunder is 3%.

Nilesh M. Patil et al., [12] proposed the new classification that focused on expanding the digital libraries very fastly. Simultaneously record them to approach this sound information. The web indexes accessible in market likewise find it trying to group and recover the sound documents applicable to the client's revenue. A computerized order framework model for music sorts are used by this approach. The first and foremost tracked down great elements for every music class. Various classifiers were prepared and used to characterize, each yielding fluctuating levels of precision in forecast. This paper has the constraint that portion utilization can't surpass at greatest use depends on 78% as it were.

The Table 2.1 shows the some of the machine learning models work together on chord classification. In that, the discussion is about some advantages and dis-advantages of the earlier models of machine learning.

Table2.1.MachineLearning Models for working on Chord Classification

S.No	Technology	Advantage	Disadvantage
1	SVM, Decision Tree, CNN [13]	Implementing multiple models for various inputs shows performance equivalent to human understanding with 91 percent accuracy.	Country, rock was not correctly classified.
2	Logistic Regression, KNN, SVM, CNN, Decision Tree [14]	ML algorithms over performed the DL algorithms	Individual study for testing genres is missing in this model.
3	KNN, NCC [15]	NCC outpaced the KNN with an accuracy of 33.5 percent.	Failed to perform on the music which contains music features like beat and flow
4	KNN, GMM [16]	Introduced the real and non-real times for feature classification with accuracies of 61% and 44%.	Cannot capture deeper melody features even with use of extraction algorithms.

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5	SVM [17]	Multi-layer SVM showed better results than Euclidian distance and other statistic algorithms.	SVM execution time is very slow, especially with a largeseveral trainingssample.
6	CNN, Random Forests, SVM, Logistic Regression [18]	Neural networks had best demonstration with accuracy of around 93 percent.	ML models outperformed DL models
7	LR,RF,XGB,SVM,CNN [19]	Gradient boosting was at its best with feature engineering and feature based classification.	The model cannot perform accurately in the presence of noisy data.
8	KNN,RF,DT,SVM,CNN [20]	Support vectors demonstrated to be good classifier.	The size and type of window alteration didn't work in terms of performance building.
9	LR,KNN,SVM,RF,MLP,CNN [21]	KNN has an accuracy of 92 percent with stretched dataset but smaller one	Analysis of features is not included in building model
10	CNN with 1D and 2D, LSTM [22]	LSTM has proved its performance with its functionality of remembering outputs	Increase in no of input signals could provide better results along with MFCC's
11	CNN,SVM,KNN [23]	A convolution kernel is developed with the integration of both SVM and KNN made its best	Including all data features may be useful in finding more patterns in the data.
12	ResNets, Transfer Learning [24]	Model's results proved to be better than the human presentation with random presumption	Feature extraction with librosa can give more accurate results.
13	CNN with pooling [25]	The accuracy of 67 percent is achieved with 4 convolution layers and SoftMax layers.	Constant value for activation function and varying weights to optimizer function could lead to better result.

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14	DNN, L1,L2- SVM, Logistic Regression [26]	The CNN is comparable to the SVM with L1 classifier in terms of performance.	Model building lacks of the signal processing and sensitivity of input data.
15	SLL, MFCC [27]	It has the best AFTE Best audio classifications Crowd Noise cancellationClassic Music	Fails Gaussian AssumptionsIncorporation of more audio classes
16	SVM, MLP [28]	Emphasizes the timePractical applicationsPowerful in classification	Adequate compromise on qualityDoes not suit automatic genre classification
17	BPNN, MFCC, SVM [29]	Shows Importance of ModellingThe average Accuracy is 43% Human accuracy increased to 53%Can be integrated into the kernel	Cannot be used in MIR fieldsAccuracy is less compared to others
18	SVM,GMM [30]	Back PropagationIncreased accuracy to 83% Better for GMM classification	Probabalamatic for a dynamic approachAccuracy is less compared to others

Table2.2.Deep LearningModelsforworkingonChordClassification

S.NO	Technology	Advantages	Disadvantages
1	SNE,MFCC [31]	The natural idea tosolve this problem iswe think of subexamples created inthe context oftheemblem method inanother context.	Slower compared toother models Complex toimplement andunderstand.
2	RNNGRULSTMSVM [32]	We can achieve atraining time of 0.23s& ofaccuracy 96%	Accepts only GTZANdataset
3	ABOOSTLDAGMMKNN [33]	Transforms one audio signal into 2D plane	Needtohavepriorknowledge ofgeneticalgraphs

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		representation.	
4	Bi-RNN, CNN, PCRNN [34]	Performance increase of genre classifier due to hybrid architecture of PR-CNN	Need more resources and power. Works only on large data sets of GTZAN
5	CNN with max pooling and average pooling [35]	Accurate factual data to the higher-level networks will be provided by integrating max pooling and average pooling.	Only one of the maximum and average pooling will be used when a single operation of pooling is performed

PROBLEM STATEMENT

Music has a significant impact on people's lives. Music brings people together who have interests and binds communities together. The type of music that people write or listen to can help to identify them as a community. Music is enjoyed by numerous organizations and groups. A crucial feature that distinguishes one style of music from another is its genre. Previously music streaming companies used to collect from music publications so to know the genre of the music through that it has been naive and hard to know user taste. So, from 2010 to 2017 music streaming platforms used to classify music based on music pitches and bases by calculating sound effects which are helpful but couldn't give appropriate results but reduced maximum effort. For the past two years as advancements in technology, they are using machine learning and deep learning which gives us a maximum approximate result regarding suggesting users' tastes or categorizing music in various separate albums based on artists, genres and by collecting user's favorite's so to suggest it to users and reach the maximum number of users.

3. NON-RD DEEP CNN Architecture:

In this Architecture, we can see initially data is undergone data cleaning process in which duplicate data will be deleted and unwanted data modules will reduce to a single dimension which is pre-processing in which we use NONRD operation which is help full for deletion of unwanted data. Later music data is sent to Feature Extraction and this will be sent to the process which are explained in implementation clearly in which convolution and pooling will take place later it will go to classification and which will give out desirable output.

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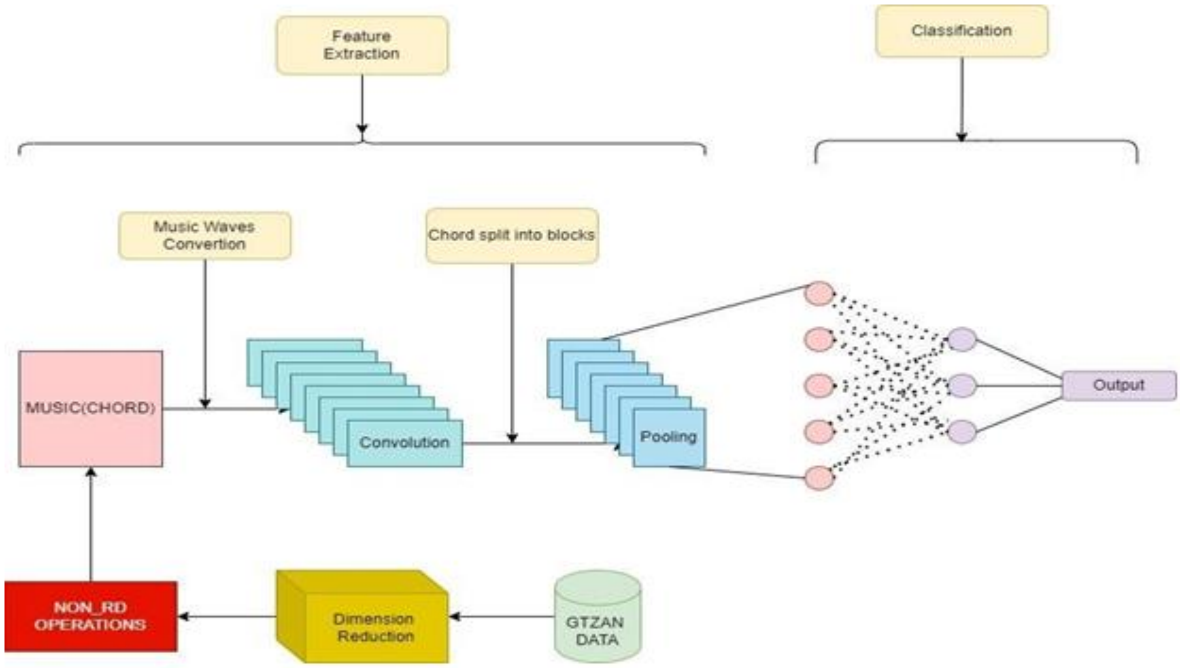

Figure 4.1 Architecture of NON-RD DEEP CNN model

NON-RD Operations:

Here in NON-RD as in the Flow chart here GTZAN data input will be given, the first whole data set will go under the data filtration of unwanted and different data types other than ".wav". Here It iterates over every data of the data set and checks whether other data formats are there or not. If yes, then it goes under deletion operation of that noise data otherwise it goes under check duplicates operation. Later, after the deletion of noise and unwanted data, it will go under the Check duplication operation. Here if any duplicates are present, it will remove that data otherwise it goes under Recheck here duplication operation is done by using their bases like labels, ID numbers same chord file which is completely done by using hash implementation. Recheck is there for filtration of data. This whole process is done in a few iterations to have the assurance that data is free from duplicates and noise operations. Later this will go under dimensionality reduction. Dimensionality reduction in the sense of reducing n dimension to n-1 or even lower greater than zero. Here dimensionality reduction is used to increase the speed and accuracy of data. So, there will be less load and more accuracy of data will be present.

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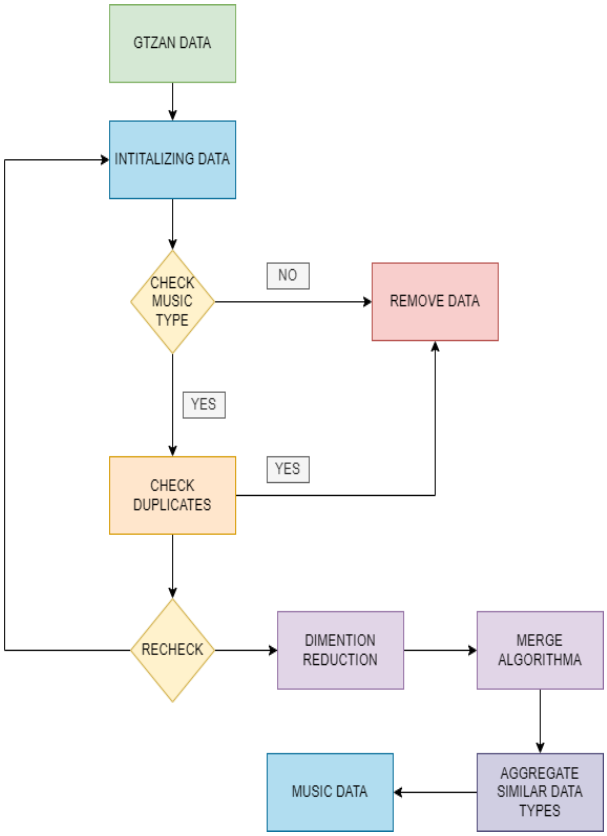

Figure 4.2 Workflow diagram for NON-RD Functionality.

Here we used the wavelet package for dimensionality reduction. After that, we will perform aggregation of music of similar labels given by wavelet, so this makes to create models and for feature extraction faster than the usual process. These results are purified and more accurate to this dataset.

4. DATA COLLECTION AND MODEL IMPLEMENTATION

The experiments are conducted by using the GTZAN dataset that consists of music data retrieval community as a default dataset. The dataset is available at www.kaggle.com/andradaolteanu/gtzan-dataset-music-genre-classification. The audio files are used prepare this dataset.

Deep-CNN Algorithm:

Step1:

//Activationfunction:ReLUAndSoftmax(transforms a value vector into a probability distribution) //

ReLUfunctionused intheconvolution layersisgiven asfollows:

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$$R(z) = \begin{cases} z, & z < 0 \\ 0, & z \leq 0 \end{cases}$$

Soft-maxfunctionused intheoutputlayer isasfollows:

$$\text{Soft-max}(z_i) = \frac{\exp(z_i)}{\sum_j \exp(z_i)}$$

where, 'z' representsthe valuesfromtheneurons oftheoutputlayer.

Step2:

//Train-ModelmethodtakesinModel,epochsandoptimizerasparameters //
//Optimizer:To minimize losses, you can modify the weights and learning rate //

$$v_t = \beta_1 * v_{t-1} - (1 - \beta_1) * g_t$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{v_t}{\sqrt{s_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

Where,

η : Initial Learning rate

g_t: Gradient at time t along ω^j

v_t: Exponential Average of gradients along ω_j

s_t: Exponential average of squares of gradients along ω_j

β_1, β_2 : Hyperparameters

5. RESULT ANALYSIS

The GTZAN dataset is made up of ten genres, each with 100 audio files, each lasting for 30 seconds. It also contains a file named as images original which contains a visual depiction of each audio track. Neural networks are one method for classifying data. To make this possible, the audio files were transformed to Mel Spectrograms, as NNs (like CNN, which we will be utilizing today) normally take in some sort of picture representation. Theaudiofilespresentinthedatasetareof '.wav' format. Fig 4.3. shows the data points distribution over the class labels.

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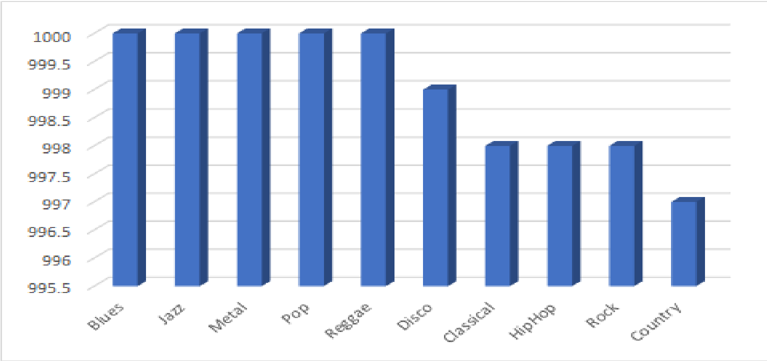

Figure 6.1 Data Points Distribution over the Classes.

Here, Fig 4.4. Depicts the amplitude of an audio file, with time (in seconds) on the X-axis and Y-axis represents the amplitude.

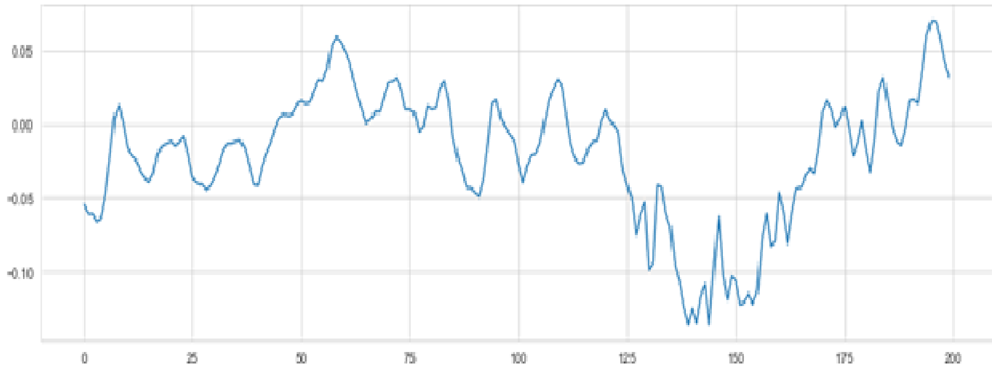

Figure 6.2 Amplitude graph for data point.

The NON-RD Deep CNN Model is implemented with the GTZAN Dataset with the size of1GB. The results were showed with parameters like, Accuracy, loss, precision, recall and F1-Score. The fig 6.3 shows the resultant values of the our algorithm

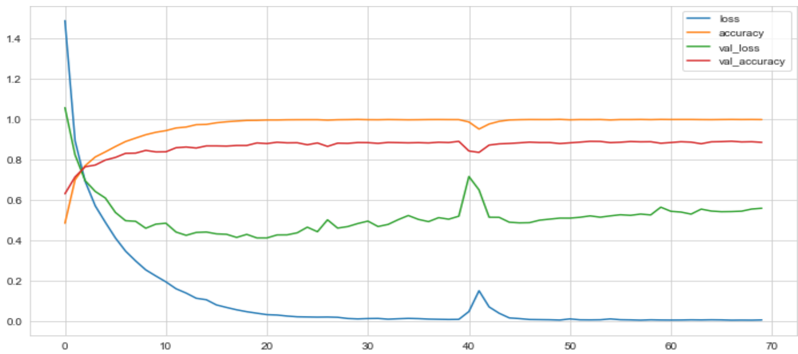

Figure 6.3 NON-RD Deep CNN Model Accuracy and Loss

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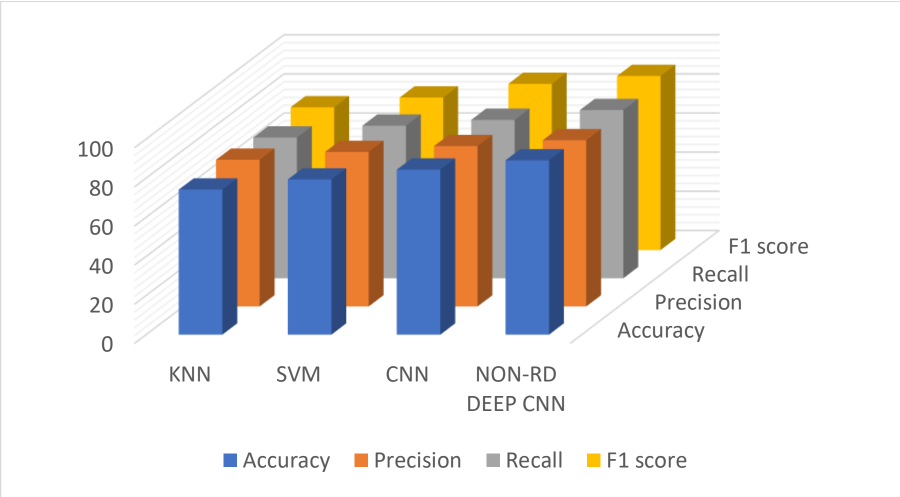

Figure 6.4 Accuracy, Precision, recall and F1-Score Comparison of NON-RD Deep CNN Model with Existing Models

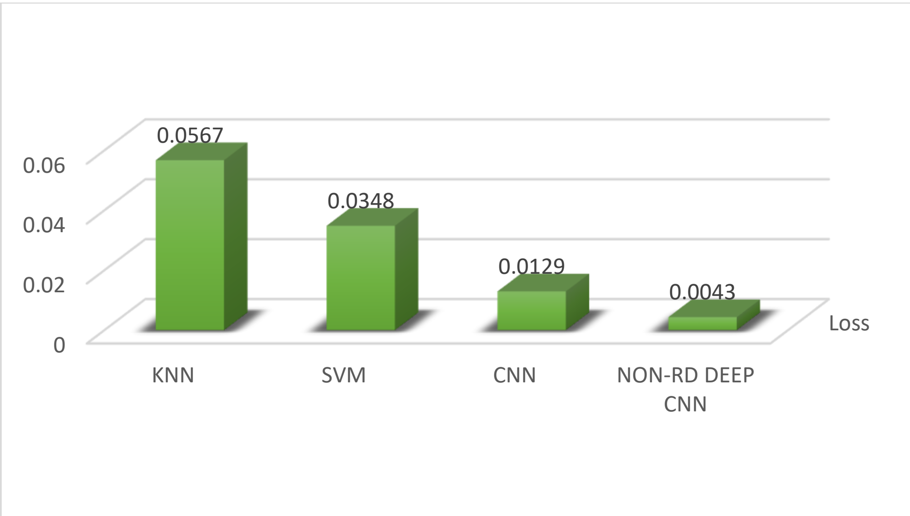

Figure 6.5 Loss comparison of NON-RD Deep CNN Model with Existing Models

The figure 6.4 and figure 6.5 shows the result comparison of NON-RD Deep CNN Model with the existing algorithms like, KNN, SVM and CNN.

6. CONCLUSION

Chord type classifiers will continue to play a key role in music recommendation and retrieval for customers of online music streaming services. With these streaming services accumulating progressively vast volumes of songs on a daily basis, developing faster and more effective machine learning models for retrieval and recommendation is critical. Deep-

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learning convolutional neural networks are compared to typical off-the-shelf machine learning models (KNN, SVM) in our research. We found that the classification accuracy for the deep learning model i.e., NONRD CNN model proved to show the best performance and obtained a pretty good accuracy compared to the other models. Furthermore, the GTZAN dataset used only has 100 samples for each of the 10 genres. The GTZAN dataset's veracity has also been questioned and proved to be a flaw. This research contributed to the use of a NON-RD_DCNN for chord type classification on the well-known GTZAN music dataset, as well as investigating how to generate more training data from existing training data by cutting audio samples into smaller samples, resulting in more samples. Our study revealed that the deep-learning models with a limited but extended dataset had superior results of the classification accuracy. The NONRD-CNN classifier, in particular, achieved astounding validation and test accuracy results at around 89.1% and a loss of 0.0043.

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