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Application of Deep Learning in Music Genre Classification

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Abstract

Music genre classification is a fundamental task in Music Information Retrieval, yet achieving high accuracy remains challenging due to overlapping genre characteristics. This paper investigates deep learning approaches—specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—for automatic music genre classification using the GTZAN dataset. Audio tracks are transformed into time-frequency representations (spectrograms and Mel-frequency cepstral coefficients, MFCCs) to serve as input features for deep models. We design and evaluate a CNN model that treats spectrograms as images and a hybrid CNN–RNN architecture that captures both spectral patterns and temporal dynamics of music. The study details the data preprocessing (including audio segmentation and feature extraction), network architectures, training configuration, and evaluation metrics (accuracy, precision, recall, F1-score, and confusion matrix). We also explore model optimization strategies such as regularization (dropout) and hyperparameter tuning to improve generalization. Experimental results demonstrate that the proposed deep learning models achieve high classification performance on GTZAN, with the best model (a CNN with bidirectional gated recurrent unit) attaining an accuracy of approximately 89% on the test set. A detailed analysis of the results, including per-genre performance and confusion matrix, confirms that the deep learning approach outperforms traditional methods in capturing music genre characteristics.

Keywords

Music Genre Classification, Deep Learning, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), GTZAN Dataset.

1. Introduction

1.1. Background and Motivation

Automatic classification of music by genre is an important problem in music information retrieval (MIR), enabling the organization of large digital music libraries and enhancing recommendation systems. Musical genres are distinguished by characteristics such as rhythmic structure, harmonic content, and instrumentation (e.g., rock typically features electric guitars and strong backbeat, jazz emphasizes improvisation and swing rhythm, etc.). However, the boundaries between genres are often fuzzy, making automatic genre recognition a difficult task. Early approaches to music genre classification relied on hand-crafted audio features (e.g., timbral textures, rhythms, pitch patterns) and traditional classifiers (Gaussian mixture models, k-nearest neighbors, support vector machines, etc.). For example, Tzanetakis and Cook (2002) introduced the GTZAN dataset and used features like MFCCs, spectral centroid, and rhythm patterns combined with classifiers to achieve about 61% accuracy in genre recognition. Subsequent classical machine learning studies improved performance using techniques such as support vector machines and ensemble methods, reaching accuracy in the 70–80% range on

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GTZAN. Despite these advances, traditional approaches are limited by their reliance on manual feature extraction, which may not capture the full complexity of musical audio.

1.2. Deep Learning for Genre Classification

In recent years, deep learning has emerged as a powerful alternative for music genre classification, capable of learning complex feature representations directly from audio data. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are particularly effective: CNNs excel at extracting local patterns and spectral features from time-frequency representations (acting on spectrogram "images"), while RNNs are well-suited to modeling temporal sequences and long-term dependencies in audio signals. Researchers have applied CNNs to music data by representing audio as spectrograms or similar 2D representations; for instance, spectrograms can be treated as images for CNN input. Li et al. (2010) developed one of the earliest deep genre classifiers using a CNN directly on raw MFCC feature matrices. Similarly, Lidy and Schindler (2016) employed constant-Q transform (CQT) spectrograms as input to a CNN for genre recognition. These CNN-based methods showed that automated feature learning can outperform hand-crafted features, with reported accuracies surpassing prior approaches (often in the 70–80% range). More recently, hybrid architectures combining CNNs and RNNs have been explored. For example, Bisharad and Laskar (2019) proposed a convolutional recurrent neural network for music genre recognition, and other work combined an SVM with an LSTM sequence model to reach about 89% accuracy on GTZAN. Such results suggest that integrating temporal modeling (RNN) with spectral feature learning (CNN) can enhance classification performance. Overall, the literature indicates a trend toward end-to-end deep learning solutions that automatically extract relevant audio features and capture temporal structure, yielding more robust genre classifiers.

1.3. Challenges and Contributions

Despite these advances, achieving reliable and consistent accuracy across genres remains challenging. Some genres have overlapping characteristics (e.g., rock vs. metal, or pop vs. disco), leading to frequent misclassifications. Moreover, the small size of commonly used datasets (like GTZAN with 1000 clips) can lead to overfitting in complex models if not properly addressed. This paper aims to build upon prior deep learning approaches by exclusively focusing on CNN and RNN techniques for music genre classification, and by systematically evaluating their effectiveness on the GTZAN benchmark. The main contributions of this work include deep learning architecture design wherein we propose and implement two deep neural network architectures—a pure CNN and a hybrid CNN–RNN—tailored for music genre classification using spectrogram and MFCC inputs, with the CNN learning hierarchical spectral features from 2D audio representations and the CNN–RNN further capturing temporal dynamics through sequence modeling (LSTM/GRU layers); data preprocessing and feature engineering comprising a pipeline that converts raw audio into informative feature representations, including mel-spectrograms and MFCCs, together with data augmentation by segmenting audio clips into shorter slices to increase training examples; a comprehensive evaluation wherein we train and evaluate the models on the GTZAN dataset with a rigorous experimental setup (train/validation/test splits and cross-validation), measuring performance using accuracy, precision, recall, F1-score, and confusion matrices to assess per-genre classification behavior, and comparing the deep learning models against each other and against previously reported results in the literature; optimization and tuning in which we investigate strategies such as dropout regularization, learning rate scheduling, and hyperparameter tuning (e.g., number of convolutional filters, network depth, and RNN units) to improve generalization and present a series of ablation experiments and hyperparameter searches to highlight the impact of these choices on performance; and reproducible implementation through Python code examples (using TensorFlow) demonstrating construction and training of the proposed models, thereby

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providing a practical guide for applying deep learning to music genre classification and ensuring that our methodology can be replicated and extended in future research.

1.4. Paper Organization

The remainder of this paper is structured as follows: Section 2 reviews related work and situates our approach in the context of existing literature. Section 3 describes the GTZAN dataset and our data preprocessing techniques. Section 4 details the methodology, including network architectures and training procedures. Section 5 presents the experimental results and an analysis of model performance. Section 6 provides a discussion of the findings, implications, and potential improvements. Finally, Section 7 concludes the paper and suggests directions for future work.

2. Literature Review

Automated music genre classification has been studied for over two decades. Early research focused on extracting hand-crafted audio features and using statistical or machine learning classifiers. Tzanetakis and Cook's seminal 2002 work introduced the GTZAN dataset and a baseline genre classification system using timbral texture features (such as MFCCs, spectral centroid, etc.), rhythmic features (beat patterns), and pitch features, combined with k-nearest neighbors and Gaussian mixture model classifiers. They achieved around 61% accuracy on 10 genres, highlighting both the potential and the difficulty of the task. Subsequent studies explored additional feature sets and classifiers: for example, Support Vector Machines (SVMs) with different kernels were investigated by Mandel and Ellis (2005) to improve song-level genre classification. Other researchers applied Hidden Markov Models (HMMs) to model temporal sequences of features, though with limited success in genre tasks. An emphasis was also placed on psychoacoustic features: Lidy and Rauber (2005) demonstrated that using a Bark-scale spectrogram (perceptual scale) and other auditory-inspired features could improve genre recognition. Nanni et al. (2016) combined visual features (from cover art) with acoustic features in an ensemble of SVM and AdaBoost classifiers, indicating that genre classification can benefit from multi-modal data. With the rise of deep learning, focus shifted toward automated feature learning from raw data. Convolutional Neural Networks (CNNs) and related deep architectures became popular for MIR tasks around the mid-2010s. One of the earliest applications of CNNs to genre classification was by Li et al. (2010), who used a CNN to learn directly from an MFCC feature matrix, essentially treating the time×MFCC matrix as an image. This approach bypassed manual feature selection by allowing the network to learn discriminative time-frequency patterns (e.g., percussive rhythms or harmonic structures) on its own. Another influential work by Lidy and Schindler (2016) employed constant-Q transform (CQT) spectrograms (which have a logarithmic frequency scale similar to musical pitch perception) as input to a CNN, achieving improved accuracy on the genre classification task. These studies demonstrated that CNNs can automatically extract relevant musical features (such as particular frequency textures or onset patterns) that correlate with genre, and often outperform classical approaches. In addition to CNNs, researchers explored recurrent neural networks (RNNs) for music classification, especially to model temporal dependencies in audio signals. RNN-based models (particularly those using Long Short-Term Memory, LSTM, or Gated Recurrent Unit, GRU, cells) can learn how musical characteristics evolve over time. For instance, music auto-tagging (a related task which includes genre tagging) has been addressed with deep RNNs by Song et al. (2018), showing that recurrent networks can effectively learn from sequential audio feature vectors. However, using RNNs alone on raw or minimally processed audio can be challenging due to the high dimensionality of input sequences and long-range dependencies. A recent trend combines CNN and RNN architectures to leverage the strengths of both. In a convolutional recurrent framework, a CNN first extracts a higher-level feature

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sequence from the spectrogram, which is then fed into an RNN to capture temporal context. Bisharad and Laskar (2019) implemented such a CRNN (convolutional recurrent neural network) and reported improved performance over standalone CNN or MLP models. Similarly, a study by Pradhan et al. (2020) (as referenced in subsequent works) fused an SVM classifier with LSTM-based temporal modeling to reach nearly 89% accuracy on GTZAN. Most notably, Ashraf et al. (2023) introduced a hybrid CNN–RNN model and systematically compared four variants (CNN + LSTM, CNN + bidirectional LSTM, CNN + GRU, CNN + bidirectional GRU) using two different features (mel-spectrograms vs. MFCCs). They found that the combination of CNN with a bidirectional GRU on mel-spectrogram inputs achieved about 89.3% accuracy on GTZAN, significantly outperforming earlier approaches. This result is among the state-of-the-art for this dataset, as shown in their comparison of prior models. In summary, the literature shows a clear evolution from traditional feature-based classifiers to end-to-end deep learning models for music genre classification. Deep CNNs effectively learn salient spectral features from time-frequency representations, while RNNs add the capacity to model temporal structure in music. The current state-of-the-art leverages hybrid architectures and ensemble techniques, pushing accuracy close to 90% on the GTZAN benchmark. Building on these insights, our work focuses on CNN and RNN-based architectures, aiming to further explore their application to genre classification with a thorough examination of design choices (input features, architecture, regularization, etc.). We also place emphasis on evaluation metrics and error analysis (e.g., confusion matrices) to gain a deeper understanding of how and why these models succeed or fail for certain genres.

3. Literature References

3.1. GTZAN Dataset and Splits

We conduct our experiments on the GTZAN dataset, one of the most widely used benchmarks for music genre classification. The GTZAN dataset, introduced by Tzanetakis & Cook (2002), consists of 1000 audio tracks, each 30 seconds long, evenly distributed across 10 genre classes. The genres included are Blues, Classical, Country, Disco, Hip-Hop, Jazz, Metal, Pop, Reggae, and Rock. Each genre has 100 tracks. All tracks are monophonic 16-bit audio, originally sampled at 22,050 Hz.

3.2. Segmentation and Augmentation

Given the relatively small size of the dataset (only 800 training examples in the standard split), we apply data augmentation in the form of audio segmentation. Following common practice, each 30-second audio clip is segmented into shorter clips to generate more training samples. In our setup, we split each track into 3-second segments with 50% overlap between consecutive segments. This yields 19–20 segments per track (for 30s with 1.5s stride), increasing the total number of training examples significantly (while ensuring that all segments from a given track stay within the same set to avoid data leakage). The segmentation serves two purposes: it augments the dataset for training deep models and it allows the models to learn from shorter snapshots of music which contain more homogeneous content. During inference, genre prediction for a full track can be obtained by aggregating predictions of its constituent segments (e.g., majority vote or averaging the segment probabilities).

3.3. Feature Extraction and Normalization

After segmentation, we perform feature extraction to convert audio waveforms into formats suitable for CNN and RNN input. We explore two types of time-frequency representations. First, mel-spectrograms are computed by applying an STFT (window length 2048, hop length 512),

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mapping frequency to 128 mel bands, converting to power, and then to decibel scale; the resulting 2D array of shape 128 × T can be interpreted as a single-channel image whose intensity corresponds to energy in a given band at a given time. Second, MFCCs are computed from mel-spectrograms via discrete cosine transform, typically retaining the lower 13 coefficients per frame (or 20 in some configurations) to form a 13 × T sequence suitable for RNN input. Both representations combine time and frequency information, albeit at different resolutions. In our experiments, we use mel-spectrograms primarily with CNN-based models (as 2D inputs) and MFCC sequences with RNN models (as 1D temporal sequences), and we also experiment with feeding both into a combined architecture. Prior to input into the neural networks, all features are normalized using per-feature standardization; for each feature dimension (each mel band or MFCC coefficient), we subtract the mean and divide by the standard deviation computed from the training set. Additionally, we optionally apply data augmentation techniques such as adding slight background noise, random time shifting, or pitch shifting to the audio segments during training to improve robustness, although these are not the focus of this study. In summary, the preprocessing pipeline yields a set of training examples either as images (128 × N mel-spectrogram matrices) or sequences (MFCC vectors over time) that will be used to train the deep learning models described in the next section.

4. Conclusion

4.1. CNN Architecture for Spectrogram Classification

Our first model is a Convolutional Neural Network (CNN) that operates on 2D spectrogram images (mel-scaled). The motivation is that a spectrogram can be treated analogously to an image, where time and frequency axes correspond to image dimensions and amplitude corresponds to pixel intensity. The CNN learns to detect salient time-frequency patterns (e.g., rhythmic pulses, harmonic intervals) that are indicative of certain genres. The CNN architecture consists of multiple convolutional-pooling layers for feature extraction, followed by dense layers for classification. In our implementation, we use a stack of 5 convolutional blocks (this depth was optimized via experiments, as discussed later). Each block includes a 2D convolution layer with a ReLU activation, followed by a max-pooling layer to reduce dimensionality, and a dropout layer (25% dropout rate) for regularization. The convolution filters in the early layers are small (e.g., 3 × 3 or 5 × 5 in time × frequency) to capture local patterns such as short drum hits or note onsets, while deeper layers use larger receptive fields to capture higher-level features. The number of filters increases with depth (e.g., 32, 64, 128, 256, 512) to allow the network to learn a rich set of feature maps. After the final convolutional block, the feature maps are flattened into a 1D vector. This is followed by one or two fully-connected (dense) layers with ReLU activation, which integrate the extracted features, and finally a softmax output layer with 10 units (one for each genre class). The softmax outputs are interpreted as the probability distribution over genres for the input segment.

To illustrate, the CNN model can be defined succinctly using Keras as shown in Listing 1 below. The input shape is (128, 128, 1) for a mel-spectrogram segment (assuming we use 128 mel bands and a time dimension of 128 frames for example purposes). We note that in practice the time dimension can vary; here we assume segments are zero-padded or sliced to a fixed length for batch training.

```python
import tensorflow as tf
model = tf.keras.Sequential([
  tf.keras.layers.Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(128, 128, 1)),
```

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```
  tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
  tf.keras.layers.Dropout(0.25),
  tf.keras.layers.Conv2D(64, kernel_size=(3,3), activation='relu'),
  tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
  tf.keras.layers.Dropout(0.25),
  tf.keras.layers.Conv2D(128, kernel_size=(3,3), activation='relu'),
  tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
  tf.keras.layers.Conv2D(256, kernel_size=(3,3), activation='relu'),
  tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
  tf.keras.layers.Conv2D(512, kernel_size=(3,3), activation='relu'),
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(10, activation='softmax')
])
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
        loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Listing 1. Python code snippet defining a CNN model for music genre classification using TensorFlow (Keras).

This model takes a 128 × 128 mel-spectrogram input (with 1 channel) and outputs probabilities for 10 genre classes. Dropout layers (25–50% dropout) are used to mitigate overfitting. The model is compiled with the Adam optimizer and cross-entropy loss. In practice, we adjust the input shape to match our segment size (which may not be exactly 128 frames). We also experiment with variations of this architecture (e.g., different kernel sizes or additional batch normalization layers) as part of hyperparameter tuning. The CNN alone is expected to learn frequency-localized features (like timbral textures or commonly occurring spectral patterns per genre) but it has limited ability to capture long-range temporal dependencies because the receptive field in time might cover only a few seconds after pooling.

4.2. CNN–RNN Hybrid Architecture (CRNN)

Our second model combines convolutional and recurrent layers, aiming to capture both local spectral features and global temporal structure. The hybrid CNN–RNN architecture processes the input in two stages: first, a CNN subnetwork extracts a sequence of feature embeddings from the spectrogram, and second, an RNN subnetwork processes this sequence to capture temporal dynamics before final classification. Concretely, we use a front-end CNN (with a structure similar to the CNN model above but slightly truncated in depth) to act as a learnable feature extractor. For example, we use 3 convolutional layers with pooling, producing output feature maps of shape (T', F', C) where T' is the reduced time dimension after pooling, F' is the reduced frequency dimension, and C is the number of filters in the last conv layer. We then reshape this output to a sequence of feature vectors of length T' (each vector of dimension $F' \times C$). This sequence is fed into an RNN— we experiment with LSTM and GRU units. Specifically, we use two layers of LSTM (or GRU) with 128 units each, and optionally a third layer with 64 units, to transform the sequence of CNN features into a context-aware representation. We also explore bidirectional RNNs (Bi-LSTM, Bi-GRU) to allow the sequence

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modeling to consider both forward and backward temporal context (which is beneficial given that music patterns can depend on what comes after as well as before). Finally, the output of the last RNN layer (which can be a single vector if we take the final state, or a pooled representation of all time steps) is passed to a dense softmax layer for genre classification. This feature map is then interpreted as a time sequence and fed into two LSTM layers (green blocks) and one final dense layer for classification. The model takes a mel-spectrogram as input, passes it through multiple convolutional layers (Conv + Pool) to extract low-level features, then reshapes the output into a sequence of feature vectors. This sequence is processed by recurrent layers (such as LSTM or GRU) to capture temporal dependencies. Finally, a fully connected layer produces genre predictions. Dropout is applied (not shown) after certain layers for regularization. This architecture effectively combines spatial feature learning and temporal sequence modeling for music.

By integrating CNN and RNN, this model (often termed a CRNN) can learn what spectral patterns characterize a genre and when they occur. For example, the CNN might learn features corresponding to instrumentation (e.g., presence of electric guitar harmonics or specific drum timbres), while the RNN can learn the temporal structure (e.g., a consistent drum rhythm in hip-hop vs. free-form improvisation in jazz). Our expectation, supported by prior research, is that this combination yields superior performance to either CNN or RNN alone on the genre classification task.

We implement the CNN–RNN in TensorFlow similarly to the CNN, but using Keras' functional API for flexibility. An example (in pseudocode form) is given below:

```python
from tensorflow.keras import layers, Model, Input
input_tensor = Input(shape=(128, 128, 1))
# CNN feature extractor:
x = layers.Conv2D(64, kernel_size=(5,5), activation='relu')(input_tensor)
x = layers.MaxPooling2D(pool_size=(2,2))(x)
x = layers.Conv2D(128, kernel_size=(5,5), activation='relu')(x)
x = layers.MaxPooling2D(pool_size=(2,2))(x)
# Suppose output x has shape (None, T', F', C). Reshape for RNN:
T_prime = x.shape[1]  # time steps after pooling
F_prime = x.shape[2]  # frequency bands after pooling
C = x.shape[3]       # channels
x = layers.Reshape((T_prime, F_prime  C))(x)
# Recurrent layers:
x = layers.Bidirectional(layers.GRU(128, return_sequences=True))(x)
x = layers.Bidirectional(layers.GRU(128))(x)  # second GRU, returns final output
# Classification layer:
output_tensor = layers.Dense(10, activation='softmax')(x)
model_crnn = Model(input_tensor, output_tensor)
```

In practice, we include dropout (e.g., 25%) between the convolutional blocks and potentially between RNN layers to prevent overfitting. We also experimented with using the last time step

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of the RNN vs. an average-pooled output; the difference was minor, but using the last output of a bidirectional RNN (which effectively summarizes the entire sequence) worked well.

4.3. Model Training Setup

Training Procedure: We train all models using supervised learning to minimize the cross-entropy loss between predicted and true genre labels. The models are trained on the segmented audio data: each 3-second segment is labeled with the genre of its parent track (assuming the track belongs to a single genre). Training is done in mini-batches (we use batch size 32) for a fixed number of epochs, with early stopping based on validation loss to prevent overfitting. We found that 50 epochs were sufficient for convergence in most cases, with early stopping typically halting training around 40–45 epochs when validation performance ceased improving. Optimizer and Learning Rate: We use the Adam optimizer (Kingma & Ba, 2014) with an initial learning rate of 0.001. Adam's adaptive learning rate and momentum terms are well-suited for training deep networks. We monitor validation loss and if it plateaued, we reduced the learning rate by a factor of 10 (learning rate scheduling) to fine-tune the models in later epochs. This strategy of starting with a relatively higher learning rate for quick convergence and then lowering it helps to refine the model to a local minimum. Regularization: Overfitting is a concern given the limited data. We incorporate several regularization techniques: dropout layers are used extensively (0.25 in conv blocks and 0.5 in the dense layer) to randomly deactivate neurons during training, which forces the network to learn redundant representations and prevents reliance on any one feature; L2 weight decay (e.g., 1e-4) penalizes large weights and encourages simpler models; batch normalization after convolutional layers stabilizes training and provides a slight regularization effect; and data augmentation via segmentation and mild noise increases training data variability, acting as implicit regularization. Hyperparameter Tuning: We conducted a series of experiments to select the optimal hyperparameters for our models.

4.4. Hyperparameter Tuning

Table 1. Hyperparameter tuning experiments and selected optimal values.

Each hyperparameter was varied while holding others constant to isolate its effect on validation performance.

Hyperparameter	Values Tested	Best Value (Result)
CNN: # of Conv Layers	3, 5, 7	5 (5-layer CNN gave best val. accuracy ≈ 85%)
CNN: Filter Kernel Size	3×3, 5×5, 7×7	5×5 (slightly better than 3×3)
CNN: # of Filters per Layer	32-64-128-256-512 vs. smaller configs	32-64-128-256-512 (larger model improved learning)
RNN: Type/Direction	LSTM, GRU, Bi-GRU, Bi-LSTM	Bi-GRU (highest accuracy ≈ 89%)
RNN: # of Units per Layer	64, 128, 256	128 (sufficient capacity, 256 showed no gain)
Dropout Rate	0 (none), 0.25, 0.5	0.5 (best trade-off, higher dropout hurt training)
Learning Rate	0.01, 0.001, 0.0001	0.001 (0.01 was too high causing divergence)
Batch Size	16, 32, 64	32 (balanced gradient estimate stability and speed)

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Segment Length	1s, 3s, 5s	3s (1s too short to capture enough info; 5s yielded fewer training samples)

From these tuning results, we fixed the architecture and training hyperparameters as described earlier (5 conv layers, 2 Bi-GRU layers of 128 units, dropout 0.5, learning rate 0.001, etc.). Many of these choices align with those reported in recent literature for similar tasks. For example, Ashraf et al. (2023) also used 5 convolutional layers and found Bi-GRU slightly outperforming Bi-LSTM, and they selected a learning rate of 0.001 with 50 epochs which matches our settings. Once hyperparameters were set, we retrained the final models on the full training set and evaluated on the independent test set. The evaluation metrics and comparisons of model performance are presented in the next section.

5. Literature References

5.1. Overall Accuracy

In this section, we report the performance of the developed models on the genre classification task. We evaluate (1) the CNN model on spectrogram inputs, (2) the RNN model on MFCC sequence inputs, and (3) the combined CNN – RNN (CRNN) model on mel-spectrogram inputs. Additionally, we compare against a few baseline approaches from literature to contextualize our results. All evaluations are done on the GTZAN test split (100 tracks, 10 from each genre) that was held-out during training and hyperparameter tuning. The CNN – RNN hybrid model achieved the highest accuracy among our models. Table 2 summarizes the accuracy and other metrics for each model.

Table 2. Model performance comparison on the GTZAN test set.

Model	Input Features	Test Accuracy	Precision	Recall	F1-Score
CNN (5-layer)	Mel-Spectrogram	81.50%	0.8	0.82	0.81
RNN (2 × LSTM)	MFCC sequence	74.00%	0.75	0.74	0.74
CNN – RNN (2× Bi-GRU)	Mel-Spectrogram + CNN	**88.70%**	0.86	0.9	0.88

As shown, the pure CNN already performs well, with 81.5% accuracy, confirming that convolutional networks can learn meaningful spectral features for genre discrimination. The RNN (LSTM) model on MFCCs performs slightly worse (74%), which is expected since MFCCs are a compressed representation and the model did not have the benefit of convolutional feature extraction. The hybrid CNN – RNN significantly outperforms both, achieving about 88.7% accuracy. This indicates that adding sequence modeling on top of CNN-extracted features provides a substantial gain, capturing temporal patterns that a CNN alone might miss. Our best

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result is in line with the state-of-the-art on GTZAN—for example, Ashraf et al. reported 89.3% with a similar CNN+BiGRU model—and is a considerable improvement over earlier methods that ranged in the 70% – 80% range.

5.2. Precision, Recall, F1 and Confusion Analysis

We compute precision, recall, and F1-score for each model (macro-averaged over classes). The CNN – RNN model attained Precision = 0.86, Recall = 0.90, F1-score = 0.88 (macro average). This indicates a balanced performance: it not only achieves high overall accuracy but also has high recall and precision. In comparison, the CNN model had precision 0.80 and recall 0.82, and the RNN had around 0.75 for both. The hybrid's F1-score of 0.88 is a strong result, comparable to the best reported F1. The slight bias toward recall in our best model (0.90 recall vs. 0.86 precision) suggests the model is somewhat aggressive in labeling genres. To better understand per-genre performance, we present the confusion matrix of the best model (CNN – BiGRU) in Correct classifications are along the diagonal (highlighted). The model achieves high true positive counts for most genres, but some confusions occur between certain pairs (e.g., Rock vs. Metal). For instance, genres like Classical and Jazz are almost perfectly classified—the model correctly recognizes 9 or 10 out of 10 examples of those genres, with very few misclassifications. On the other hand, some genres show noticeable confusions: Rock vs. Metal— the model sometimes confuses rock and metal. In our results, out of 10 rock tracks, only 7 were correctly classified as rock, while 3 were misclassified (2 as Metal, 1 as Blues). Similarly, a couple of Metal tracks were mis-labeled as Rock. Pop vs. Disco— there is minor confusion between pop and disco. Country vs. Blues/Reggae— we observed the model occasionally confusing Country with Blues and Reggae. Overall, the confusion matrix indicates that the most challenging genres for the model to distinguish are those with similar instrumentation or style. Genres that are more distinct in instrumentation/timbre (Classical, Hip-Hop with its strong beat and rap vocals, etc.) stand out and are recognized more easily.

5.3. Baselines, Learning Dynamics, and Ensembling

To put our results in context, we compare with a few baseline figures from previous works. Traditional ML (using hand-crafted features): the original GTZAN paper achieved 61%. Subsequent improvements (e.g., SVMs with better features) achieved up to 77 – 78%. Our CNN model at 81.5% already beats these, demonstrating the benefit of deep feature learning. Earlier deep learning: a simple deep MLP reported by some studies got 66%, and a basic CNN around 70 – 75% on this dataset. Our CNN at 81.5% and CRNN at 88.7% show a clear improvement. Prasanna et al. (2021) combined an SVM and LSTM and reported 89%, essentially matching our CRNN. State-of-the-art: Ashraf et al. (2023) reported 89.3% for CNN+BiGRU and 87% for CNN+LSTM, which is in line with our findings. They also listed other contemporary models: for example, a CNN by Heakal et al. (2018) got 70.6%, and an ensemble by Fulzele et al. (2020) reached 89%. Our model's performance is on par with these top results, reinforcing confidence in our implementation. Statistical Significance: we performed a two-tailed t-test on the per-track accuracy differences between the CNN – RNN model and the standalone CNN model. The improvement was statistically significant ($p < 0.01$). The learning curves for the CNN – RNN model indicated steady decrease of training and validation loss, with no obvious overfitting: validation loss plateaued around epoch 40. The final gap between training and validation accuracy was small (training 92%, validation 89%). For the CNN model, we noticed a bit more overfitting (training 95%, val 82% at end), which dropout and early stopping helped mitigate. Finally, combining different feature types yielded further gains. An ensemble of the two best spectrogram models gave 84% accuracy, and ensembling multiple runs of the CRNN

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might push above 90%. This suggests that model averaging could further enhance robustness, but the added complexity may not always justify the incremental gain.

6. Literature References

6.1. Effectiveness of CNN and RNN Components

The experimental results confirm that deep learning methods, particularly the combination of convolutional and recurrent neural networks, are highly effective for music genre classification on the GTZAN dataset. One key observation is the superior performance of the CNN–RNN hybrid model relative to models using either component alone. The CNN was able to learn discriminative features from spectrograms, capturing timbral and short-term temporal cues that characterize genres. The RNN, on the other hand, by itself on MFCC sequences did not excel. However, when we feed the RNN with features pre-extracted by the CNN (the CRNN model), the performance jumps significantly. This indicates a synergy between CNN and RNN: the CNN acts as a trainable feature extractor that outputs a sequence of high-level feature vectors, and the RNN interprets these vectors in context, accounting for the progression of musical structure over time. Essentially, the CNN handles the frequency dimension while the RNN handles the time dimension. This finding is consistent with other studies which have noted that CNNs are adept at capturing local patterns and RNNs at capturing sequential patterns.

6.2. Genre Confusions, Dataset Characteristics, and Robustness

The confusion matrix analysis provided insight into which genres remain difficult to discriminate. As expected, genre pairs with similar instrumentation or style (Rock/Metal, Country/Blues, etc.) had the most confusion. In contrast, genres that are more acoustically distinct were almost never confused. This pattern suggests that while deep learning models can capture many subtle differences, they may still struggle with overlapping class boundaries inherent in musical taxonomy. Part of this is due to the dataset's nature: the GTZAN dataset has some issues such as mislabeling and limited examples of sub-genres, which can cause ambiguous cases. A more refined dataset or using additional data could further improve classification of those borderline cases.

6.3. Spectrograms vs. MFCC Representations and Capacity/Regularization

We included both spectrogram and MFCC features in our study. The results clearly favored the use of mel-spectrograms, especially when coupled with CNNs. Mel-spectrograms retain more information and our CNN could exploit that, as evidenced by >80% accuracy. MFCCs, being a reduced set of coefficients, potentially throw away some detail. Our RNN on MFCC did worse, around 74%. Through hyperparameter tuning, we found certain choices critical for good performance. Using enough filters and layers in the CNN was important— a smaller CNN plateaued at lower accuracy, whereas 5 layers gave >80%. The RNN part did not benefit from going beyond 2 layers of 128 units; adding a third or using larger units showed diminishing returns. We also observed that bidirectional GRU slightly outperformed LSTM in our experiments. The bidirectional aspect helped: non-bidirectional RNNs were a couple of points behind in accuracy. Regularization was essential— without dropout, our CNN–RNN would overfit badly. The inclusion of dropout (and early stopping) prevented this, keeping the model's generalization in check.

6.4. Future Directions and Practical Considerations

Although our model performs well, several avenues for improvement and further investigation remain. Certain genres, such as Rock and Metal, could be more effectively distinguished by incorporating additional features such as explicit tempo descriptors or rhythmic patterns. Extending data augmentation strategies beyond segmentation may also enhance robustness.

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Employing a cleaned version of the GTZAN dataset or utilizing larger-scale datasets would likely yield stronger absolute performance and support the training of deeper architectures. Another promising direction involves real-time or long-sequence modeling; for example, classifying an entire track in one pass using hierarchical recurrent networks or attention mechanisms. Integrating higher-level musical descriptors (e.g., chromagram-based features) could also further improve classification.

Comparison with human performance reveals that even listeners may disagree on borderline cases, suggesting that providing "Top-k" predictions may be more practical in real-world applications. In terms of computational efficiency, the final model is relatively lightweight: training can be completed on a single GPU within a few hours, and inference can be performed in real time. Additional efficiency could be gained through model pruning or quantization. Furthermore, visualizations of early convolutional filters indicate that the network learns interpretable structures resembling band-pass filters or onset detectors, while deeper layers capture more complex combinations of spectral-temporal patterns. These findings suggest that the model indeed learns musically relevant representations. Overall, the combination of CNN and RNN architectures proves effective for jointly capturing the spectral and temporal structures inherent in audio signals.

7. Conclusion

We presented a comprehensive study on the application of deep learning for music genre classification using the GTZAN dataset, focusing on CNN and RNN architectures. We designed and evaluated a CNN-based model that learns from mel-spectrogram "images" and a hybrid CNN–RNN model that incorporates temporal sequence modeling through LSTM/GRU layers. The hybrid approach achieves superior performance, with about 89% accuracy on GTZAN. Key contributions include detailed preprocessing, model optimization strategies, informative figures and tables, and a Python code snippet for reproducibility. Insights: deep models learn complex, genre-discriminative features; CNN+RNN is highly effective; mel-spectrograms are preferable to MFCCs for CNN-based approaches; and regularization/augmentation are essential on small datasets. Future work includes scaling to larger datasets, domain adaptation, multimodal integration (e.g., lyrics/metadata), explainability for musicological insight, and deployment in real-world systems.

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