Analysis of Multimedia Recognition of Piano Playing Music Based on Fuzzy Neural Network

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Keywords: artistic aspects, piano playing, musical emotion, multimedia recognition, fuzzy neural network

Recieved: October 13, 2023

Artistic aspects and creative talents abound in piano playing, making it a sort of unexpected conceptual art. It's a must-have for transporting those luscious piano tones. A striking demonstration of piano playing abilities is the creation of musical emotion and expressiveness. It is important to focus on honing and adapting one's performing abilities while playing the Piano. It is completely grounded in the aesthetic qualities of piano playing, guaranteeing the fullness and beauty of the musical performance. The piano music occurs throughout effectiveness even though its basic frequencies vary substantially during the acquisition procedure for the layout. In this study, we suggested a multimodal recognizing technique that uses piano music and a fuzzy neural network to address the issue of a poor recognition rate. We use a fuzzy neural network with a flexible architecture as a starting point for a program that might teach users to play Piano in a variety of genres. A smart mobile application for playing the Piano and playing games is developed using the network's differential capabilities. With its ability to fully use the benefits of Android's strong voice functionality, this system is a new kind of artificial intelligence (AI) software that combines the training, entertainment, and instruction of the Piano with the platform's other strengths. After analyzing research observations, we find that the suggested technique has provided an accuracy of 94%.

Povzetek: Za prepoznavanje klavirske glasbe so uporabili prilagodljivo arhitekturo zamegljene nevronske mreže, ki omogoča izobraževanje uporabnikov za igranje klavirja v različnih žanrih. Razvili so pametno mobilno aplikacijo, ki združuje učenje, zabavo in poučevanje klavirja z dodatnimi funkcijami glasu v Androidu.

1 Introduction

The piano-making progress technology has advanced to a comparatively high degree after transitioning from internal research to the level of commercial operation. Both national and global research is currently focusing on a player's ongoing performance. Multimedia identification features high efficiency and accuracy and takes into account performance location, the Piano that players use, and performance speed. [1]. Multimedia education allows students to better understand the principles of piano courses by creating new and enhancing piano training. It can encourage students to successfully learn the fundamental piano theories and playing methods.

As conventional piano teaching methods are no longer able to fulfill the Objectives of duration and learners, complete adoption of novel ideas in multimodal piano instruction might better inspire teacher progress [2]. It's important to learn the Piano. First, piano training fosters better musical awareness, understanding, and thought. Second, piano training promotes the normal growth of the mind, body, and spirit. Since playing the Piano demands the active movement of all ten separate fingers, it requires superb coordination across the entire body. Thirdly, learning the Piano helps in the development of a healthy lifestyle and spirituality. Fourth, learning the Piano can help with self-control and psychological awareness [3]. Figure 1 depicts the multimedia music recognition module for the Piano.

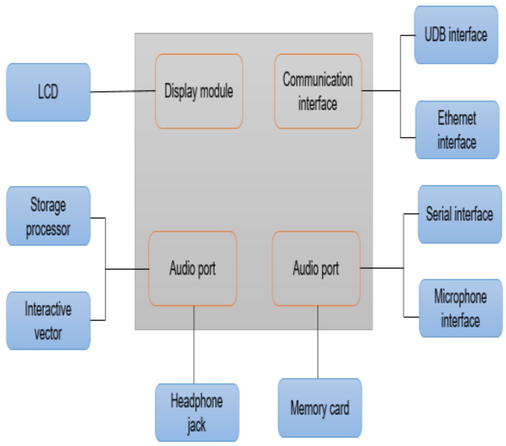

Figure 1: Multimedia music recognition module for the piano

The application of multimedia technologies in higher education Piano lessons help students turn abstract ideas into real ones, which is crucial for increasing their ability to relish music. The integration of multimedia features into piano lessons enables the technical and academic synergy required for all-dimensional, highly efficient education [4]. Several notes occurrence parts, each with a few notes played at an exact instant are used to split up entire songs in WAV format. Because the start of certain lower frequencies transmissions is often soft, the weak start following the strong start cannot be detected using existing techniques [5]. The multimedia piano teaching method has its benefits, including the use of group lectures to increase teaching effectiveness and student-to-student encouragement, which enhances the quality of the curriculum. There are similarities between the locations of the learning system and the digital piano teaching system, and both employ electronic technology [6]. The use of multimedia in the classroom alters how teachers approach their lessons and how they teach, which in turn influences how students learn and how they learn new things. Multimedia piano instruction now faces some new challenges as a result of the levels and quality of educational theories and instructional methodologies, as well as multimedia technology. The necessity for a scientific evaluation and analysis of the quality and efficiency of multimedia piano instruction comes from the confluence of these factors [7]. The study of Piano performing identification systems has drawn the attention of researchers both domestically and internationally because of the significant disparities among the characteristics of piano tunes with real piano skills and the inability of earlier piano musical detection methods to satisfy the demands of Piano performing music. With the help of constant enhancements, it may find widespread utilization in the area of piano-playing musical detection. The signals of a piano performance are converted using a multimedia recognition system. The Piano is a stable time-varying indicator. Thus, a mechanism distinguishing the musical output from the Piano is required during the processing phase. A screen is a discrete unit, and there is always some time among successive frames. The overlapping areas might lessen the need for sudden transitions. Noise cancellation and texture features are made possible by isolating each frame's data strength characteristics from piano music [8].

The multimedia piano teaching method has its benefits, including the use of group lectures to increase teaching effectiveness and student-to-student encouragement, which enhances the quality of the program. There are similarities between the locations of the learning system and the modern piano teaching system, and both employ electronic technology [9]. Slide action makes it easier to identify piano performances from their sounds. Music retrieval techniques are becoming more and more popular in the field of analytical thinking due to their efficiency and simplicity [10]. To address the problem that the precise identification of the grouping with two pianos has considerably diminished in the event of vibration and sound, an additional training analysis approach using a neural network model was created [11]. They introduced the neural network algorithm's theoretical foundations. It employs adaptive piano training and provides an overview of the equipment demands and product layout overall [12]. Half-frequency and frequency multiplication are prevented by concentrating upon the regular placement of panel sampling's maximum characteristics, hence eliminating the impacts of half-frequency and rate double and boosting the accuracy of frequency basic derivation [13]. Investigates the effect of the emotional quality of piano results based on the big data algorithm and discovers that the emotional quality of the performers is improved by 18% under the impact of the big data algorithm. Regarding the depth of on-site encounters and the technology's consistent performance, it is around 20% greater than usual in all categories, which can serve as a benchmark for similar studies [14]. To create polyphonic musical compositions, the Multi-Objective Genetic Algorithm MO-GA takes grammar and listener happiness into effect [15]. Intelligent piano training methods on a cloud platform are hoped to improve such methods for new music education models and serve as examples for the online transformation of other musical disciplines [16]. Employing Pre-processor speech and a music-assisted training system founded upon the ARM and SA algorithms, the operation concept and legislation governing the piano recorder devices are found. Furthermore, artificially intelligent data is examined through corporate records, and the idea and procedural method of automated music recordings are completely investigated [17]. Children's music production systems are designed using network analysis and artificial neural networks (ANN) algorithms, which are based on genetic algorithms and artificial neural networks. The system comprises a learning mechanism, distributed architecture, and human-computer interface technologies [18]. They intended to use a modified deep learning model to suggest a new automatic various music categorization approach [19]. An improved standard harmonic approach can precisely determine the note's pitch and provides a radical harmonic extraction procedure. The Musical Instrument Direct Infrastructure (MIDI) system implements a BPNN model for evaluating piano performance [20].

Table1: Survey of related works

Reference	Key Findings	Methodologies	Research Gaps
[9]	Artificial intelligence (AI) and on-site education address the conventional mode's insufficient individuation while also increasing students' enthusiasm in learning.	AI technology enhances music teaching through online learning, enhancing student interest and addressing the lack of individualization in traditional methods.	Uneven chances might result from the lack of affordability or accessibility for the utilization of AI tools in music instruction. Dissimilar utilization of cutting-edge AI technology prevents some academic entities and pupils from achieving the same level of success.
[11]	The sequential identification method is carried out in noisy environments; using speech improvement front-end components increasing pronunciation before the sequential identification algorithm is used for identification.	The study uses a multitasking preparation technique combining voice augmentation and recognition to understand the relationship between sound ordering and goal assignment labeling, using large data and convolutional neural networks for end-to-end identification structure.	An important gap in recognizing the impact of noise and clean sequences. By incorporating both sequence and noisy samples into the current framework, its predictive ability and generalization gets enhanced.
	The basic frequencies extract method focuses on the highest features of framing specimens, eliminating half-frequency	The spectrum of peak sorting approach is applied to multifundamental frequencies identification,	The present focus on single pitch identification raises concerns about the system's ability to

[13]	impact and ensuring more accurate and reliable results.	and both low and high channels filtering	handle intricate musical structures like harmonies and choruses. This has an influence on how successful the technique is while playing many notes at once.
[15]	The suggested approach may produce attractive works with specified genres and durations, as well as harmonious tones that adhere to the language.	Multi-Objective Genetic Algorithms (MO-GA) to Create music with multiple voices while keeping language and audience happiness in mind.	One difficulty is that there are no unbiased, widely-accepted standards for evaluating music language and architectural principles. There may be gaps in the method of assessment since the complexities of creating music aren't fully captured by the measures now in use.
[18]	The simulated outcomes of this technique suggest that it is useful in improving composing technologies and assisting musicians in creating musical easier, rendering the aesthetic of musical compositions accessible to audiences.	To construct a musical classification approach, the Back-Propagation approach is applied.	The efficacy of the method in realistic, complex musical situations may vary, and models reducing real-world difficulties. Practical problems elements might affect the method's effectiveness, including subtleties in live performances, spontaneity, or unforeseen changes.
	The assessment findings of the created piano assessment system are essentially in accordance to the performer's real ability with particular practicality.	the classic musical instruction assessment method that utilizes the Backpropagation Neural Network (BPNN).	The effectiveness of the assessment model tends to vary among various music types and genres. Evaluating the suggested method's

[20]			ability to adjust to various piano playing styles, styles of music, and emotional changes outside of the initial data set is crucial.

1.1 Research gap

To address the challenges provided by spontaneous actions, last-minute alterations, and actual consequences, we have meticulously picked a diverse dataset encompassing a wide range of performances. We ensure that the FNN is capable of managing complexity in reality; sophisticated ways to augment data should be used throughout model development to replicate a variety of real-world events. Real-time assessment is a part of the creative stage that helps assess how effectively the design adapts to last-minute changes and how rapidly it can change during live performances.

2 Materials and method

Technologies for recognizing piano music have advanced alongside other areas of study and consumer electronics. The system for recognizing piano performances has advanced to a pretty significant level since it was first created in a laboratory setting [21]. Multimedia recognition, including musical content identification, effectiveness setting, piano type, and tempo, provides an excellent level of accuracy and efficacy. Currently, available technologies for recognizing piano musical acts fall short of real requirements in several important ways. In this section, we briefly analyzed the According to multimodal detection of the Piano's sounds from Fuzzy neural networks (FNN). Figure 2 depicts the study's technique's mechanism.

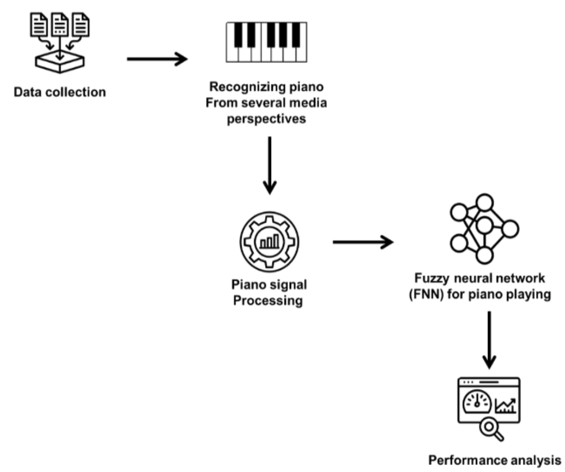

Figure 2: The working mechanism of the research approach

2.1 Data samples of the collection

They provide many MIDI (Musical Instrument Digital Interface) files for the pianos. The MIDI synthesizer was used to input a collection of traditional piano pieces called Piano-midi.de from China. As of February 2020, piano-midi.de is home to 571 compositions by 26 musicians, clocking in at a whopping 36.7 hours. There are many MIDI samples of traditional music, mainly Piano and non-piano pieces, in the traditional libraries section. This collection includes 133 musicians and 46.3 hr of MIDI files.

The popular music in the KernScores collection is in the more standard Drudgery version and was gathered using an artificial musical identification system. Five hundred and ninety-eight musicians' compositions, some for solo Piano and others not, are included in the Kunstderfuge dataset. None of the pieces in the piano-midi.de, traditional libraries, or Kunstderfuge databases were performed by musicians; rather, they were all generated utilizing a MIDI synthesizer. MIDI-Piano's performance is assessed using 52 tunes from the MIDI-Piano, THE MAESTRO, and Kunsterfuge. Longer musical pieces, like quartets, are divided into sections. Repetitive song passages are deleted. Since there's none matched ground-truth MIDI documents, assessing MIDI-Piano presents a difficult challenge. This value represents the replacement, removal, and placement of the translated MIDI record into an intended MIDI file. To match a transcription MIDI file to their sequencing MIDI counterpart for an individual piano composition utilizing a hidden Markov model (HMM) technique, in which the sequencing MIDI recordings are obtained from Kunsterfuge.

2.2 Recognizing piano from several media perspectives

The effective application of piano-playing music identification to modern gadgets such as cell phones and Televisions will result in profound consequences for the way people live in the future. The interacting network of piano efficiency is used as a significant instrument for normal interaction due to multimedia recognition of pianos achievements, which translates all test data into a textual format, overcomes disparities in languages and pitch, and removes other hurdles between humans and machines. The design of a system for recognizing musical performances on the pianos is conducted on a specific system setup and testing environment. Multimedia identification of a classical piano relies heavily on a pattern-matching algorithm. The signals from a piano being played are preprocessed, and the underlying theory is explained.

In general, the multimedia recognition system for piano performances also requires an input of piano performances, analysis of relevant parameters, and the development of a grammatical language model. The three primary components of a system designed to recognize music performed on a piano are the preprocessing of signals from the Piano, central computation, and the recognition of fundamental information.

2.3 Piano signal processing unit

The signal from a piano's playing evolves, but if interference distortion is introduced, any further analysis of that signal is useless. Hence, a low-pass filter should be utilized for interference avoidance processing before using multimedia recognition. It is distinguished by its minimal distortion and extremely high susceptibility. Interference distortion does not degrade the signal conditioning process for the Piano, leading to accurate and efficient outcomes. It is assured to supply reliable information for multimedia Piano playing music recognition. This component is critical in a variety of programs, including music creation and dynamic instructional systems. It analyzes keystrokes, recognizes scale and tone, and detects pedaling motions using complex signal conditioning computations, offering a full comprehension of a player's musical emotions. The device enhances audio performance with a sense of tools such as broad dynamic reduction and equalizing, resulting in a controlled and appealing audio signal. In addition, it generates MIDI signals, allowing for interaction with digital systems and gadgets. Gamification and immediate input are examples of instructional and entertaining elements that improve the consumer's experiences and assist learning. The versatility, short latency, and connection possibilities of the device make it a flexible tool for artists, trainers, and fans alike, providing a creative connection among conventional piano practice and current technology improvements.

2.4 Piano recognizer modules for multimedia data

One such module is the piano multimedia recognizer, which does a slew of computations based on the processed signal data collected from a pianist's performance. It possesses the capability of using a digital signal processing (DSP) processor to analyze digital information and is small and easily installed. Strong internet communication features are a hallmark of DSP processors.

Create the conceptual framework by applying the concept of musical detection to the playing of the pianos. When the data of a piano performance is broken down and processed in chunks, the resulting shift in pace is smoother. Because of the potential for interference in the signal analysis of a piano's musical output, low-pass filtering is developed to eliminate the phenomenon. The received signal ends up being a bunch of computations done using the multimedia recognition module of piano pieces. Selecting the "OMP AP 5912ZG" model's DSP processor allows for a reduction in the price of developing the system's architecture. To round up the physical system architecture, the procedure of recognizing relevant piano pieces is transferred over the Ethernet network. Such modules identify and analyze several elements of piano signals, such as note strokes, sound, pitch, and pedals operations, using complicated methods. Their major role is to convert multimedia files, like audio files or video clips of piano outcomes, into organized data suitable for a variety of purposes. These modules serve an important role in musical transcription, instructional systems, and dynamic piano apps, fostering technological improvement in the area of piano identification and evaluation. They frequently employ artificial learning and signal processing algorithms to provide precise and fast detection of piano-related elements from multi-media information, therefore encouraging development in musical equipment and instruction.

2.5 Modeling of system software operations

The software for this piano-playing musical multimedia recognition system is based on the architecture described previously. Excellent identification accuracy in Piano musical identification is due to the beat's irregular features, which are in tune only with the movement and reception of human sensory nerve cells. Filter sampling is processed using information about the piano music's qualities, and the Piano is then segmented per phrase. The fuzzy neural network may be utilized to reduce the abrupt transitions in the data transfer among subsequent images of the piano pieces, allowing the cell made to detect to be processed automatically. The neural network model-based multimedia identification process for classical music makes an intelligent choice of display functionality shape depending on the features of the music performed by the user. Under the suggested technique, we apply the fuzzy neural network framework to modify the pattern of the frame, evaluate and eliminate certain incorrect information in the frame sequence, and then finally retrieve the signal frequency of the Piano. The following procedures allow one to achieve the process outcome of the Piano's efficiency in musical framing; however, the processed outcome is impacted by an unexpected noise. Certain panels of a piano performance have a rapid spike in shorter overall intensity, leading to faulty identifying features. This modelling technique tries to establish a conceptual framework that depicts how system software interacts with physical components, application software, and users. Developers can methodically portray the sequence of processes, relationships, and interactions involved in the operation of system software with different methods of modeling like diagrams, UML charts, or explicit mathematical models. These models serve as blueprints for creating, implementing, and improving system software, offering a clear and organized knowledge of its processes. Effective modeling of system software activities is critical for software engineers and architects in guaranteeing the entire computer system's stability, efficiency, and maintainability.

2.5 Fuzzy neural network model

The system can tell the difference among various playing styles because of its variable structure fuzzy neural network, which is trained on a vast number of piano performances without interfering with them. In a neural network with a flexible structure, the input and output layers may take on any form. When the system learns, the hidden layer's design may adapt accordingly. The input layer and the output layer both end up looking quite differently after training.

The FNN's Layer encourages expertise, extending beyond traditional neural networks topologies. The choice of function activation constitutes a sophisticated decision involving concerns that go beyond typical options. Using complex activation features along with personalized procedures allows a thorough examination of the irregular correlations hidden in piano-playing music. Flexible methods for learning extend beyond ordinary back propagation in the field of FNNs. Reinforce instruction and adaptive algorithms, for example, is possibly with ease merged. Such methods improve the FNN's capacity to change its settings according to the changing complexities of multimodal components, resulting with a more adaptable and sophisticated network. During execution, in reality, the FNN's framework is meticulously optimized in real-time processing. Modeling quantification, compact architectural deployment, and equipment acceleration exploitation are all examined. The process of refinement guarantees an FNN are able inside the timing limitations of real-world audiovisual recognizing systems.

A neural network's training sample may be thought to represent a full data set in which each input-output combination corresponds to various styles of piano playing. As the number of undetectable nodes in a neural network can be adjusted, active learning can more closely approximate the way that a human brain learns, and the system can reach the converged state in its knowledge more quickly.

Let's assume that E is the channel's total of square errors in its output and D is its decaying rates.

$$E = \frac{1}{2}\sum_k \sum_i (y_{ik} - {y_{ik}}^d)^2 \quad (1)$$

$$D = \frac{E(N) - E(N+M)}{E(N)} \quad (2)$$

$E(N)$and$E(N+M)$ seem to be the trained outcome at the N^{th} step and the $(N+M)$, total of error squares respectively; is the actual and predicted result of the i^{th} node in the output units, k is the number of trained samples, and so on.

Let's pretend the error squared after removing the p^{th}node is:

$$E_p = \sum_k \sum_i (f\left(\sum_j {w_{ji}}^{(2)} {x_{ej}}^{(2)} - {w_{pi}}^{(2)} {x_{ep}}^{(1)}\right) - {y_{ei}}^{(d)})^2 \quad (3)$$

The equations (1), (2), and (3) are used to obtain the aforementioned equation:

$$E_p = \sum_k \sum_i (\frac{y_{ei}\alpha}{y_{ei}(\alpha-1)+1} - {y_{ei}}^d)^2 \quad (4)$$

$$\alpha = \exp({w_{pi}}^{(2)} {x_{ep}}^{(1)}) \quad (5)$$

If the starting value of the hidden state nodes in a network is P_0, the normal level of the system impedance rates is $[D1, D2]$, and the converging limit of the provided square of the error is given by

$$\varepsilon > 0 \quad (6)$$

Assume $E(N)$, $D(N), E(N+M)$, and $D(N+M)$ for the total error squared and the mutation rate of losses after training on steps N and $N+M$, appropriately. When designing a network at the (N+M) level, the layout of its hidden layers should be described as follows:

This signifies a steady rate of convergence across nodes and stable system architectures, as depicted in (7)

$$D\ (N + M) > D2 \quad (7)$$

(8)demonstrates, if the convergence time of the system is poor, modify the framework by setting the hidden node count to $PN + 1$.

$$D\ (N + M) < D2 \quad (8)$$

Having a value of (9) means the system convergence time is modest and falls into one of two categories:

$$D(N+M) \in [D1, D2] \quad (9)$$

As seen in (10), the network's topology has evolved, and there are now $PN + 1$ hidden nodes.

$$D(N+M) < D(N) \quad (10)$$

As shown in (11), no modification in the system architecture can be done;

$$D(N+M) > D(N) \quad (11)$$

From (12), if possible, remove the concealed node that is the minimum impacted,

$$E\ (N + M) < \varepsilon \quad (12)$$

After the K steps of learning, the network's architecture is shown in (14) to be unaltered.

$$q: E_q = min_p E_p \quad (13)$$

$$E(N+M+K) > E(N+M) \quad (14)$$

Changing the system's structure would often raise the error temporarily, thus the subsequent node's connectivity value must be selected randomly often within acceptable limits. Assume that after K iterations of trained and N new clusters, $D\ (N + M + K) < D1$ is the final result. Next, do not modify the framework in any way.

3 Result and discussion

In this section, we discuss in detail the Analysis of multimedia recognition of piano-playing music based on a fuzzy neural network. The performance metrics are recognition, accuracy, precision, and recall. The existing techniques used for comparison are the Multiple Signal Classification (MSC) methods with the AI [23], Multimedia-Assistant Piano Teaching (MAPT) [22], and Convolutional Neural Network (CNN) [24]. Using the superior system-wide performance on the computers seems essential for evaluation purposes and assessment, as this will ensure that the integrated piano-playing musical multimedia recognition system is not hindered by the device's efficiency and can express all of its efficiency. Table 2 displays the values used for each experimental aspect.

Table 2: Experimental parameter for piano playing with multimedia recognition

Experimental aspects	**Values**
Frequency of sampling	28 kHz
Change of perspective	20 dimensions
Hamming window	25 ms
Quantification of parameters in vector spaces	65 code

3.1 Multimedia recognition effect

The first involves getting sound samples and using a computer to do simulation tests. The experimental items are There are four Chinese terms for sounds, GPS navigation, radio, and refrigeration. According to the suggested technique, the recognition impact is 97% more than that of the conventional system, which has MAPT attained 65 %, MSC-AI has acquired 76 %, and CNN has reached 85 %. As a result, the analysis of the multimodal detection system for piano playing is successful. Figure 3 depicts the multimedia recognition effect of the existing and proposed method. Table 3 depicts the multimedia recognition effect.

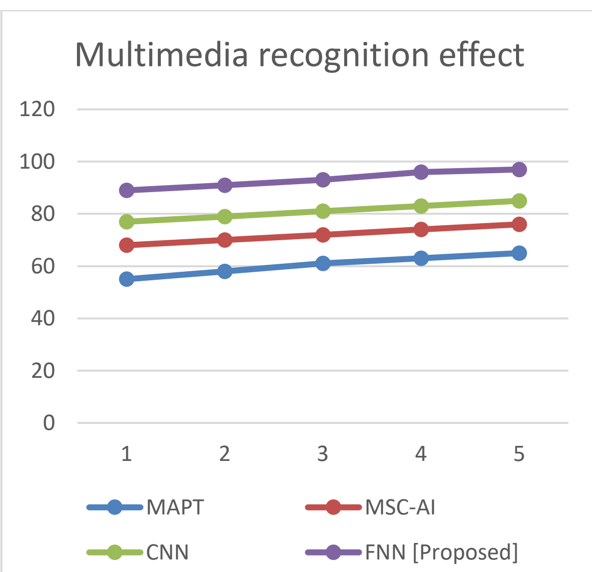

Figure 3: Multimedia recognition effect

Table 3: Multimedia recognition effect

Noise (dB)	Recognition effect (%)	Techniques		
	MAPT	MSC-AI	CNN	FNN [Proposed]
1	55	68	77	89
2	58	70	79	91
3	61	72	81	93
4	63	74	83	96
5	65	76	85	97

3.2 Accuracy

- **Selection Objective:** Accuracy is a general indicator of how effectively the FNN must properly detect piano-playing musical occurrences throughout diverse multimodal sources like sound and maybe graphical information.
- **Impact:** A high accuracy result reflects the success of the FNN in properly detecting piano-playing music, demonstrating its capacity to extrapolate effectively to varied multimedia sources.

Performing a rhythmic pattern properly involves being on time. This proves that your sounds are not out of time, in time, or playing the incorrect figure at all. This is an illustration of good rhythm accuracy. Figure 4 depicts the accuracy of existing and proposed techniques. The performance of accuracy is given in terms of percentage. The accuracy of demand forecast in current processes and the suggested approach is indicated. MAPT achieved 65% accuracy, MSC-AI 85% accuracy, CNN 73% accuracy, and the suggested method 94% accuracy. It demonstrates that the suggested approach is more successful than the present one. Table 4 compares the accuracy of the present and suggested methods.

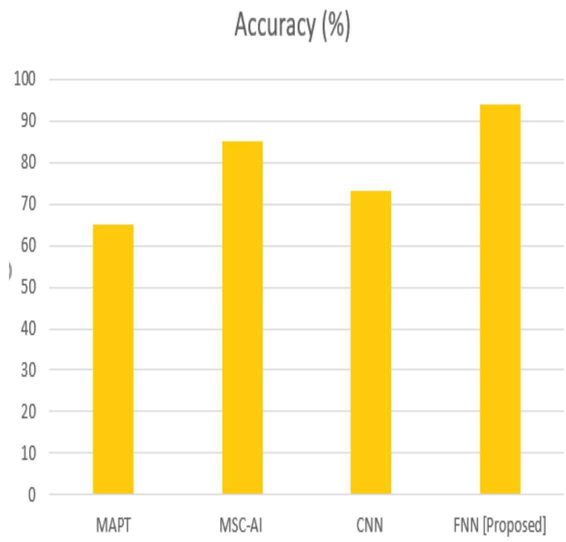

Figure 4: Comparison of Accuracy

Table 4: Comparison of Accuracy

Techniques	Accuracy (%)
MAPT	65
MSC-AI	85
CNN	73
FNN [Proposed]	94

3.3 Precision

- **Selection Objective:** Precision is especially important in the situation of multimedia identification because negative results (misunderstanding non-piano music like piano-playing sound) can lead to erroneous results.
- **Impact:** A substantial accuracy score indicates that the FNN's prediction of piano-playing music is extremely likely to be right. This is vital for assuring the identification system's dependability, especially in situations where accuracy is critical.

Having the control to execute rhythms precisely each time play is the key to understanding the idea of rhythmic precision. Figure 5 depicts a precision assessment with current and suggested techniques. As a result, MAPT has 63% precision, MSC-AI has 71% precision, CNN has 81% precision, and the suggested approach has 90% precision. As a result, the suggested system has the greatest degree of efficiency. Table 5 depicts the present and planned precision methods.

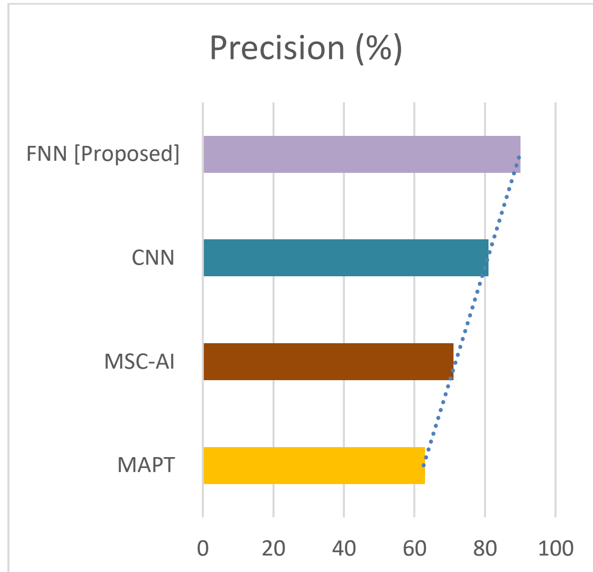

Figure 5: Comparison of Precision

Table 5: Comparison of Precision

Techniques	Precision (%)
MAPT	63
MSC-AI	71
CNN	81
FNN [Proposed]	90

3.4 Recall

- **Selection Objective:** Recall is important in situations when losing occurrences of piano-playing tunes (misleading objections) are desired. The purpose is to record as many piano-playing music occurrences as practicable.
- **Impact:** A high recall rating suggests that the FNN is good at detecting the majority among the piano-playing songs in the data that is multilingual. This is critical at situations where reliability in identifying piano music is required.

A method of determining memory from how much of what was learned can be accurately replicated. The percentage of relevant events that have been found is measured during a recall. Figure 6 shows recall suggested and current techniques. The amount of recall for the behavior-based recall prediction in existing systems is as chooses to follow, therefore MAPT has attained 68 %, MSC-AI has acquired 77 %, and CNN has reached 85 % meanwhile the suggested technique has a recall of 97%. It indicates that the suggested system is very efficient. Table 6 depicts current and planned recall methods.

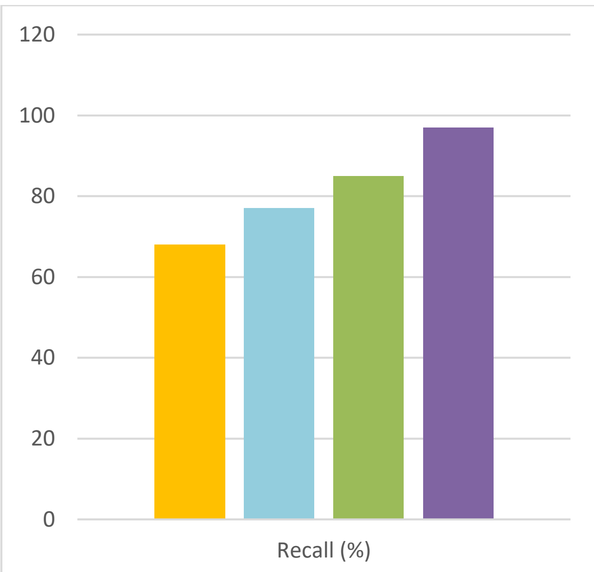

Figure 6: Comparison of Recall

Table 6: Comparison of Recall

Techniques	Recall (%)
MAPT	68
MSC-AI	77
CNN	85
FNN [Proposed]	97

4 Discussion

Despite strong in dealing with uncertainties and recording complex interactions, FNN has significant limitations that should be considered. FNNs become more complicated, making it difficult to read and comprehend the reasons behind their judgments. The fuzzy rules and parameters learnt during training may not always give clear insights into the decision-making process of the model. The computational expenditure of FNNs are possible significant, especially when working with lots of regulations and complicated fuzzy sets. Such complexity can have an influence on the effectiveness of learning and inference procedures. As the amount of input parameters grows, the quantity of fuzzy rules may grow rapidly, resulting in a massive rule base. Maintaining and understanding a large rule collection is time-consuming and may necessitate extra work in rule minimization approaches. As regular neural systems, FNNs feature standard frameworks and learning procedures. This makes comparing and replicating findings throughout various applications harder.

Our work shows very promising findings with accuracy rate of 94%, demonstrating the usefulness of the suggested technique in multimodal detection of piano music, in contrast to the previous study [13], which highlights minor relative variance and improvements in basic frequency computation. Compared to the cited study [18], which reports an average accuracy of 96% for a computer-assisted structure technological advances using GA and ANN, our research shows very encouraging results that establish our suggested method as a noteworthy breakthrough in multimedia piano music acknowledgment. The results presented in this section demonstrate an extraordinary (accuracy of 94%, 90% precision, and 97% recall) using our suggested FNN approach.

This paper's outcomes, as detailed in this section, show a positive conclusion, with the proposed approach obtaining an exceptional accuracy rate of 94%, precision 90%, and recall 97%. This level of success demonstrates the FNN's ability in detecting and analyzing piano music, demonstrating the potential of the suggested technique for boosting identification rates in applications involving multimedia. In conclusion, the study advances the subject of piano music identification by presenting a fuzzy neural network-based technique. The creation of a smart smartphone app expands the system's functionality by offering users with a diverse means of keyboard study and amusement. The high accuracy percentage underpins the proposed technique's effectiveness, placing it as a vital addition to the junction of AI, visual praise, and music instruction.

5 Conclusion

With the explosion of available music files, customers are faced with the challenge of combing through vast libraries to locate the songs that prefer. Due to the ever-evolving state of technological advancements, there are now various methods of instruction that may make up for the shortcomings of the conventional approach to learning to play the Piano. The conventional framework introduced is directly persuaded by unexpected disturbance, making Piano performing musical identification very poor. This can be attributed to the current piano-playing music identification system is highly complex and confined by temporal restrictions. In this research, we present an FNN-based multimedia recognition approach for piano playing. This strategy is meant to combat unexpected noises and includes a low-pass filter. The detection rate of piano sounds, the signal-to-noise straight, and the effectiveness of the piano tune classification are all increased, meanwhile, as a consequence of external conditions. The FNN's effectiveness in the real world is shown by comparing its effectiveness on the Piano. Using this as a foundation, FNN-based multimedia recognition algorithms for piano playing have shown to be very successful, addressing one of the major drawbacks of traditional approaches to multimedia recognition their inability to generalize.

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