

Real-Time Gesture Recognition for Virtual Musical Instrument Control Using Binary Finger Encoding

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Abstract:

This paper presents a real-time hand gesture recognition system for virtual musical instrument control, designed to make music creation more accessible, expressive, and cost-effective. Using a standard webcam and MediaPipe-based hand tracking, the system converts five-finger combinations into binary codes, allowing for 32 distinct gestures. These gestures can be freely mapped to piano notes or drum sounds through an interactive Streamlit interface. Pygame enables multi-channel audio playback, allowing for rapid, overlapping notes, while adaptive frame skipping maintains real-time responsiveness across devices. A key feature is the gesture customization system, which allows artists to define their own controls and download a personalized cheat sheet for reference. Unlike existing gesture- music systems that rely on specialized hardware, this approach requires only a webcam, making it highly portable and affordable. The system successfully supports performance of real melodies such as “Happy Birthday.” Future work includes dual- hand control for chords and melody, predefined gesture mappings, and deployment as a cloud-based, mobile-responsive platform. This solution represents a significant step toward democratizing digital music creation through low-cost, intuitive, and inclusive design.

IndexTerms: Gesture recognition, binary encoding, real- time interaction, assistive music technology, human-computer interaction.

I. INTRODUCTION

For tens of thousands of years, music has been an essential component of human culture. Bone flutes from the Upper Paleolithic period are among the archeological finds that indicate musical expression has existed for at least 40,000 years [1]. Over time, musical instruments evolved from primitive percussion tools to complex mechanical and electronic devices, each extending human capability for rhythmic and melodic communication. In modern societies, music continues to serve as a vital form of entertainment, therapy, and personal identity.

However, access to musical creation is still uneven, though. Common traditional musical instruments including pianos, guitars, or drum kits call for significant financial commitment, physical dexterity, and extended training time [2]. Moreover, such instruments can be large, non-portable, and inaccessible to people with motor impairments or disabilities [3]. Although digital audio workstations and electronic instruments have expanded the creative terrain, they still create learning challenges and typically call for physical interfaces like keyboards, MIDI controllers, or touch-screens.

Researchers and developers have looked at gesture-activated musical systems in order to remove some obstacles. These let artists trigger musical sounds with body motions rather than actual instrument contact. Systems like Kagura, EyeHarp, and MuGeVI have demonstrated the potential of gesture-based interaction for inclusive musical performance [4] [5] [6]. However, many such systems rely on external hardware such as gloves, depth cameras, or infrared sensors, increasing cost and reducing portability [7]. Recent advances in computer vision and machine learning have enabled real-time, marker-less hand tracking using standard RGB cameras. Google's MediaPipe framework provides accurate 2D hand landmark detection and finger position tracking in real time, using only a webcam [8]. This development makes it possible to design touch-less musical instruments that are cost-effective, portable, and intuitive. This paper introduces a webcam-based virtual musical instrument system that uses binary encoding of finger gestures to control piano notes and drum sounds. It employs MediaPipe for hand tracking, Pygame for multi-channel audio playback and live animation, and Streamlit for a real-time interactive interface. Each hand gesture is represented by a 5-bit binary code based on the state (extended or not) of each finger, resulting in 32 unique gesture combinations. These gestures can be mapped to sound outputs, allowing artists to play music through natural hand movement.

A. Motivation

To provide music-making opportunities to a larger population, including those with physical disabilities, is a central drive behind this effort. Conventional instruments pose serious barriers for people with disabilities because their construction normally takes for granted full physical mobility, excluding participation on an inclusive basis [9]. Additional hindrances to accessing music-making are the economic costs of purchasing musical instruments and receiving professional instruction, which can be unbearable for many individuals [10]. Traditional music performance typically demands a lot of formal schooling, practice, and technical knowledge, thus precluding those without professional training from enjoying fully expressive music creation [11]. Thus, the primary motivation behind this project is to remove these barriers and democratize musical expression.

In addition, this work seeks to provide an intuitive, customizable interface that is based on minimal hardware, i.e., a regular webcam and a computer and only a mobile phone in the future, to translate hand gestures into musical outputs. The system can be easily adapted to accommodate various artists' preferences and capabilities so that it remains usable and interactive on an individual basis [12]. This accessibility is especially important considering the documented therapeutic and social benefits of music; engaging in musical activities has been shown to reduce stress, support emotional health, and strengthen social connections and cultural bonds [13]. Therefore, making music participation more inclusive holds significant artistic, personal, and societal value.

B. Problem Statement

Traditional musical instruments, even with their expressiveness, have a number of inherent disadvantages. They are generally very costly, requiring huge sums of money; they also need extensive formal training and considerable bodily dexterity, which bars most aspiring musicians [10][11]. For example, young people and adults with lower socioeconomic status often find it too expensive to buy and keep instruments, curtailing their music prospects [10]. Most traditional instruments are also physically demanding and not portable, thus making them infeasible to those with motor impairments or mobility issues [9]. Moreover, acoustic instruments tend to be relatively inflexible in modifying their interface or the sound they produce to suit people's preferences or capabilities, hence limiting their usability inclusively [12].

Gesture-based musical instruments have arisen as viable substitutes to overcome these impediments, seeking to make music-making more intuitive, expressive, and inclusive [4][6]. Gesture recognition or

other input alternatives like eye gaze have been used in systems that effectively enabled artists with extreme physical impairments to be creatively involved in music-making, hence expanding musical involvement [5][6]. The interfaces leverage natural movements or gestures instead of the usual physical interactions with the instrument, substantially reducing initial barriers to usability.

Nonetheless, current gesture-based musical systems still have key problems hindering their performance and broader usage. Numerous existing platforms merely offer fixed pre-defined gesture collections with no features for artist-adjusted customization, requiring users to conform to sanctioned interactions instead of adapting to natural preferences or needs [14]. In addition, these systems are frequently not implemented with built-in visual feedback or open "gesture-to-sound" cheat sheets, and additional cognitive burdens are put on artists who need to commit gesture mappings to memory, resulting in greater error and frustration for beginners [15]. In addition, some gesture-based interfaces rely on proprietary hardware, depth sensors, sensors, or highly controlled environmental settings, limiting realistic usability and accessibility in varied, everyday situations [7][16]. Finally, most current gesture-based interfaces are not very expressive and flexible for new musicians or people with disabilities, unwittingly recreating the learning curve inherent in conventional musical instruments and hence potentially excluding target user groups [14][16].

These constraints indicate an obvious requirement for more flexible, inclusive, and intuitive gesture-based musical systems, driving this research's objective to develop an accessible, user-customizable, and hardware-independent musical interface.

C. Contributions

This paper presents several technical and usability-oriented contributions to the field of gesture-controlled musical interaction systems:

We implement a low-latency hand-tracking pipeline using only a standard webcam and Google's MediaPipe framework, which detects 21 landmark points per hand to enable real-time gesture recognition. Unlike prior systems that rely on specialized hardware such as data gloves or depth cameras, this approach achieves reliable performance using widely available consumer-grade equipment, improving scalability and affordability [17].

The system introduces a 5-bit binary encoding scheme in which each finger's position—extended or closed—is mapped to a binary value. This structure allows $2^5 = 32$ unique gesture combinations per hand, offering a scalable and computationally lightweight method for triggering musical events [18].

Our system has two standalone modes—piano and drums—with gesture-sound mappings unique to each. In contrast to earlier gesture-based systems simulating only one instrument type per interface [19], our two-mode design offers greater expressive ability and user interaction.

The system utilizes the Pygame audio mixer to allocate individual gesture-activated sounds to multiple channels, which allows them to be played together. This allows overlapping notes and chords to be played by the user, accommodating polyphony and percussive layering—crucial functionalities lacking in single-channel gesture instruments [20].

To provide real-time responsiveness, the system adapts frame processing rates dynamically depending on computational load. By skipping frames under high load, it ensures smooth tracking and avoids lag. This optimization is particularly useful for lower-end systems and is an extension of performance adaptation methods employed in real-time computer vision applications [21].

A user interface provides the ability for performers to map gestures to audio files of their preference. The mappings are stored within a JSON format, providing flexibility to tailor the instrument to various musical scales, instruments, or accessibility requirements—contrasting with fixed-gesture systems

where mappings are hard-coded [22].

The system creates an in-performance "cheat sheet" that maps every binary gesture to its respective sound label in real-time. This reduces the cognitive load for new artists and allows for rapid learning and reference during performance.

It is intended to operate using just a webcam and ordinary computer, making the system conform to low-cost, inclusive design principles. It does away with the cost and hardware impediments of devices such as MIDI controllers or motion sensors and is therefore more appropriate for people with financial or physical disabilities. This is in line with the increasing demand for accessible digital musical instruments (ADMIs) for inclusive music-making [9].

D. Paper Structure

Section II provides a literature review and reviews previous work in gesture-controlled musical systems and accessible digital instrument design. Section III describes the theoretical basis of the proposed system, such as binary gesture encoding and its integration with music theory. Section IV explains the system methodology, including gesture tracking, adaptive frame control, and user interaction mechanisms. Section V covers implementation details like the software architecture, user interface, and gesture-to-sound mapping logic. Section VI analyses system performance in terms of latency, recognition accuracy, and usability. Section

VII presents empirical results from user testing and live demonstrations. Section VIII discusses possible future extensions, such as dual-hand interaction, larger instrument libraries, and cloud deployment. Lastly, Section IX concludes the paper by highlighting key contributions and reiterating the system's ability to facilitate inclusive and expressive music making. **RELATED WORK**

The intersection of gestural interaction and music performance has inspired various systems that explore expressive and accessible music-making. These systems span vision-based interfaces, gaze-controlled tools, wearable devices, and educational instruments designed for artists with diverse needs.

A. Vision and Camera based Instruments

Vision-based interfaces use camera input to track user movement and translate it to musical output. Technologies like Microsoft Kinect use structured infrared light to provide full skeletal body tracking to enable real-time music composition using dynamic movement [23]. The Leap Motion Controller uses two infrared cameras and LEDs to track precise hand and finger movement in three dimensions, frequently with custom DAW integrations or Max/MSP interfaces [24].

More recent systems have transitioned towards standard RGB webcams. For instance, Kagura works on 2D or 3D camera input and computer vision-based gesture tracking and mapping to visual symbols on the screen that activate audio samples and effects [4]. Kagura has the potential to enable real-time gesture recognition with no wearables or physical controllers. MuGeVI relies on extending the vision-based interaction with Google's MediaPipe hand tracking to identify 21 landmarks on the hands and translate them into different types of musical interaction, including performance, accompaniment, control, and effects [6].

Both systems are compatible with MIDI or OSC output to ensure synthesizer and digital audio workstation compatibility. The underlying benefit of camera-based instruments is that they are hardware-independent. Precise gesture recognition can be temperamental under low light or busy backgrounds, though. Substantial advances in lightweight, highly accurate gesture tracking (e.g., MediaPipe) have made responsiveness and usability much better [17].

B. Eye Tracking Interfaces

Eye-controlled instruments are designed to emphasize hands-free interaction, mainly for those with severe motor impairments. EyeHarp, for example, translates direction of gaze (recorded through an eye

tracker or webcam) into musical notes or chord choices on a graphical interface [5]. The system separates its interface into melody and harmony layers and employs a dwell timer or blink detection to fire events. EyeHarp has internal synthesis and MIDI support, making integration with external sound engines possible. It operates on open-source software platforms and supports users in varying scale, instrument timbre, and interface sensitivity. Although highly accessible, these interfaces can have low expressivity and cognitive overload with extended use [5].

C. *Sensor and Tactile based Instruments*

Some interfaces employ other types of sensors for input, thereby enhancing accessibility via touchless or tactile input techniques. Soundbeam employs ultrasonic sensors to sense proximity and movement. It converts movement in terms of distance into MIDI messages, enabling artists to play notes by moving their bodies or limbs within an invisible "sound field" [25]. The technology is extensively employed in special education and therapy environments for people with limited fine motor skills.

Skoog is a pressure-sensitive tactile foam cube that includes internal sensors that can detect squeezes, presses, and twists. This cube creates a Bluetooth connection to a program that translates these inputs as musical notes or sound effects and thereby enables children as well as individuals with physical disabilities to utilize it adaptively [26].

Wearables such as the Mi.Mu Gloves have flex sensors (for finger bends) and IMUs (for orientation and motion). The gloves send sensor data wirelessly to software (like Glover) to enable the artists to apply highly expressive hand gesture to MIDI/OSC signal mappings [27]. Mi.Mu gloves are employed in live professional performances and offer haptic feedback, gesture calibration, and personalized mappings.

D. *Summary of Gaps*

Despite the innovations described, current gesture-based instruments face key limitations. Many rely on expensive or specialized hardware like depth cameras, ultrasonic sensors, or wearable electronics [25][26][27]. Eye-tracking systems provide accessibility but often lack expressive control and require calibration or external devices [5]. Vision-based systems such as those using MediaPipe still demand robust lighting and computing conditions, and earlier camera-based tools lacked finger-level tracking [4][6][17].

Another persistent gap is the lack of flexible, user-defined gesture mappings. Most interfaces offer fixed or hard-coded gesture-to-sound pairings. Configurability often requires technical expertise, making it inaccessible to general artists. Few systems combine low-cost hardware, real-time responsiveness, and easy customization. A solution using a webcam, binary-coded gesture mapping, and an intuitive UI—while supporting dual instrument modes and downloadable cheat sheets—could provide a new standard for inclusive, expressive, and affordable music interaction.

II. THEORETICAL BACKGROUND

A. *Binary Gesture Encoding*

Our system encodes each hand gesture using a 5-bit binary number, where the binary state of each finger—raised

(1) or not (0)—is used to define a gesture. Each bit in this sequence corresponds to one of the five fingers on a human hand, with the thumb assigned the least significant bit (LSB) and the pinky the most significant bit (MSB). The bit positions and their respective weights are outlined in Table I.

To compute a unique gesture ID, the system performs a weighted sum of the bits where fingers are raised. For example, as shown in Fig 1, if only the thumb and pinky are raised, the resulting binary sequence is 10001, which equals:

$$(1 \times 2^4) + (0 \times 2^3) + (0 \times 2^2) + (0 \times 2^1) + (1 \times 2^0) = 16 + 1 = 17$$

TABLE I- BINARY ENCODING OF HAND GESTURE

Finger	Bit Position	Binary Weight	Power of 2	Decimal Value (If Raised)
Thumb	0 (LSB)	00001	2 ⁰	1
Index	1	00010	2 ¹	2
Middle	2	00100	2 ²	4
Ring	3	01000	2 ³	8
Pinky	4 (MSB)	10000	2 ⁴	16

Thus, gesture 17 corresponds to this specific combination. This gesture ID is then used as a key for indexing sound mappings stored in a JSON file, enabling modular assignment of musical notes, drum samples, or other effects.

The binary-to-decimal encoding mechanism not only allows for compact and efficient representation but also inherently supports the system's customization ability. Artists are able to remap audio files to any gesture ID via the interface, and these new mappings are retained in the configuration JSON, supporting reproducibility and user-specific expressivity. The theoretical maximum of 32 unique gestures (i.e., 2⁵) per hand offers a balance between cognitive load and expressive ability. This can be increased to 1024 (2¹⁰) if both hands are used independently, allowing for flexibility in future system upgrade. The compact gesture representation also enables lightweight computation, allowing for real-time music generation feasibility without the need for high-end hardware [18].

B. Music Theory Integration

The proposed gesture-controlled musical interface is built on foundational principles of Western music theory, enabling expressive melodic, harmonic, and percussive performance through a finite set of 32 binary-coded gestures. These gestures align with musical constructs such as notes, chords, and drum components, making the system both theoretically sound and practically effective. Western tonal music is structured around the 12-note chromatic scale, with each note representing a semitone step. An octave encompasses 12 distinct pitch classes (e.g., C–C#–D–...–B), after which the sequence repeats at a higher frequency. Many compositions use diatonic subsets of this chromatic set, such as the C major scale (C–D–E–F–G–A–B), consisting of seven notes that define tonality [2]. Given 32 gesture possibilities, the system can support two full chromatic octaves (24 notes), with additional gestures available for other musical controls or instrument sounds. This range is consistent with many compact MIDI keyboards used in live and educational settings [12].

Western chords are created by stacking thirds. A triad is a root, a third, and a fifth (C–E–G), and seventh chords and more add an extension to the stack for more complex harmony [10]. The chords can be translated to single gesture IDs with binary codification. For in the binary code 00011 (thumb and index fingers up) maps to decimal 3 and can be translated to a particular chord such as C major, and other combinations accommodate minor, diminished, or suspended chords. The expressive but space-efficient gesture set allows for this mapping in a scalable fashion.

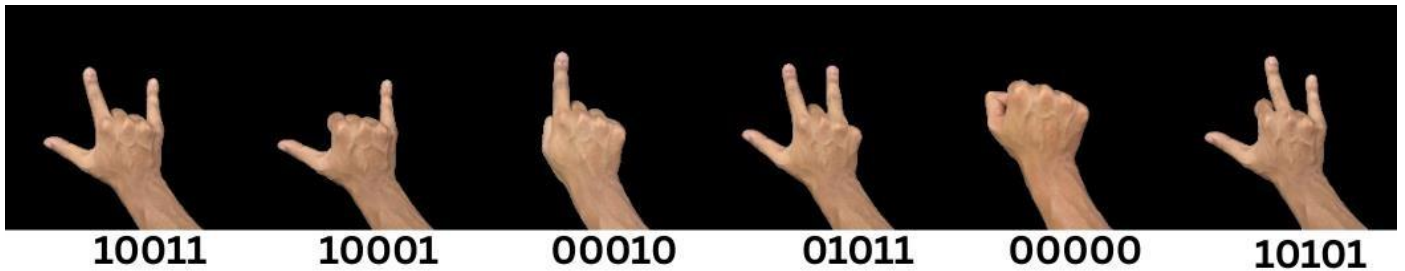


Fig. 1. Examples of hand gestures with their corresponding 5-bit binary representations based on finger states (thumb to pinky). These binary codes are used to generate unique gesture IDs for sound mapping in the system.

The system also includes a polyphonic playback engine, allowing multiple notes to be played simultaneously using Pygame’s multichannel audio mixer. This supports sustain, an essential musical effect in which a note or chord continues to resonate after it is played. Sustain enhances expressivity, especially in piano or ambient sound contexts. Technically, sustain is achieved by maintaining the audio playback for a specified duration or until the user changes gestures, rather than cutting off the sound abruptly—an important feature for realism in virtual instruments [20].

In percussion, a typical drum kit consists of components such as the snare, kick, toms, hi-hat, and cymbals, all contributing to the rhythmic foundation of music. The 5–7 instruments in most kits can be successfully mapped onto the

32 gesture slots. The capacity of the system to deal with overlap of gestures and multiple audio channels enables layered percussive articulation, such as playing the kick and snare simultaneously—feature lacking in monophonic or single-mapped instruments [7].

As a demonstration of feasibility, the system can play back the melody of "Happy Birthday," one of the more ubiquitous exercises in beginning music instruction. The piece is written to simple rhythmic structures and a major scale over an octave, and thus it is an ideal piece for building pitch accuracy, reaction to timing, and gesture mapping effectiveness. Additionally, it has been regarded by many as a cultural standard by which to measure beginning proficiency across musical instruments [1]. By building the system on these foundation music theory structures—pitch, harmony, rhythm, and sustain—the gesture-controlling device illustrates that a highly limited gesture set can give rise to a rich, expressive musical performance. The binary encoding model not only limits input processing but also creates a natural point of integration with theoretical models of music, adding both accessibility and artistic richness.

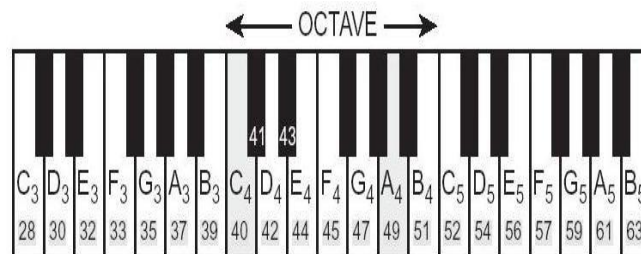


Fig. 2. Visual layout of a standard piano keyboard showing the 12-note chromatic scale and the concept of octaves. Middle C (C₄) and A₄ (440 Hz standard) are labelled, along with MIDI note numbers. This diagram illustrates how gesture IDs from the binary system can be mapped effectively to musical notes across octaves.

III. METHODOLOGY

A. System Overview

The proposed system is a real-time gesture-to-music interface built on a structured multi-stage processing pipeline (see Fig. 3.). It begins with webcam input, which provides continuous live video frames. These are handled with MediaPipe Hands, a machine learning library that can track 21 hand landmarks per hand in real-time even on humble computational hardware [8].

The identified landmarks are handed over to a gesture logic module, which computes the state of each finger is either "raised" or "down" by analyzing the geometric constraints between the position of the fingertip and the lower joints. This logical representation encodes the hand structure into a 5-bit binary string, one bit per individual finger, ordered from thumb (least significant bit) to pinky (most significant bit). The binary string is mapped into a decimal gesture ID ranging from 0 to 31. This numerical representation is essential in allowing the gesture classification simplification and in assisting custom mapping mechanisms later in the processing pipeline [18].

Every gesture identifier is associated with a target audio file by a mapping table in a JSON configuration file. This method provides flexible gesture-to-sound mapping assignment or re-assignment. Subsequently, the target audio file is streamed to a Pygame based multi-channel audio mixer to support simultaneous playing of multiple audio channels for polyphonic sounds and complex percussive effects [20].

Lastly, a Streamlit based interface enables the system to be interacted with. It contains instrument choice (drums/piano), gesture remapping, and visual feedback capabilities, allowing the system to be both performable and easily accessible to beginners. The structure possesses low latency and great accessibility through the utilization of a typical webcam and web-based interaction.

B. Hand Tracking using MediaPipe

MediaPipe Hands is a real-time hand-tracking framework developed by Google that uses a two-stage machine learning pipeline to localize 21 keypoints (landmarks) on a detected hand per video frame using standard RGB webcam input [8][17]. These landmarks represent major anatomical reference points including the wrist (landmark 0), metacarpophalangeal joints (MCP) – the base knuckles (e.g., landmark 5 for index finger), proximal interphalangeal joints (PIP) – the middle joints (e.g., landmark 6), and the fingertips (TIP) – the terminal ends (e.g., landmark 8 for index finger), as illustrated in Fig. 4.

The system detects the palm bounding box first and afterwards uses regression in order to retrieve accurate hand landmark coordinates. The three values in each landmark consist of: (x, y) image frame-normalized positions, and an relative z-depth value reflecting the distance the landmark is away from the wrist landmark (0) [8].

To label the binary state of each finger (up = 1, down = 0), spatial comparisons are among prominent landmarks:

For the index, middle, ring, and pinky fingers, the system assesses the vertical (y-axis) location of the TIP (for example, landmark 8 for the index finger) with respect to the PIP joint (for example, landmark 6). If the condition $y_{TIP} < y_{PIP}$ holds, the finger is labelled extended or "up."

With the thumb, which is more horizontal in orientation, the classification is along the x-axis. More precisely, the TIP (landmark 4) is taken with respect to the MCP joint (landmark 2). In a right hand, if x_{TIP} is smaller than x_{MCP} , the thumb is labelled as elevated; this is reversed for left hand specific configurations [17].

Each hand movement is thus represented by a 5-bit binary vector (thumb to pinky), giving 32 different combinations from [00000] (fist) to [11111] (fully open palm). This binary gesture ID is an input to downstream modules such as gesture- to-sound mapping and UI feedback.

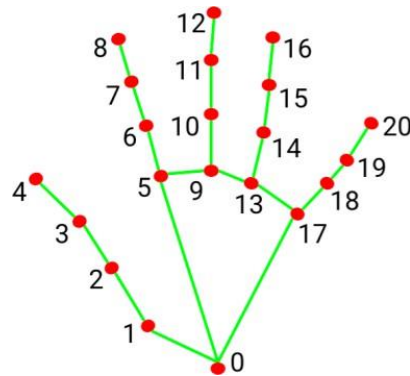


Fig. 4. MediaPipe hand landmark model output showing 21 labelled points across the hand. Landmarks 4, 8, 12, 16, and 20 represent the fingertips (TIP), while landmarks 2, 6, 10, 14, and 18 correspond to the PIP joints. Thumb extension is computed by comparing the x -coordinates of TIP (4) and MCP (2); other fingers are evaluated via vertical distance from TIP to PIP

MediaPipe is designed for high-speed execution even on low-end hardware and supports real-time tracking over 30 FPS. Its landmark estimation model is optimized both for accuracy and speed, with robust performance in partial occlusion and changing illumination conditions [17][21].

C. Adaptive Frame Skipping

To maintain real-time responsiveness and system fluidity, the proposed gesture recognition pipeline employs an adaptive frame skipping algorithm. This mechanism dynamically adjusts the number of processed video frames based on current computational load, thereby preserving low latency even under hardware constraints or during heavy system use.

Let f_{target} represent the target frame rate (e.g., 30 Hz),

yielding a nominal frame interval of $T_{target} = \frac{1}{f_{target}}$

. For each

captured frame i , the system measures its processing duration T_i , which includes time spent on hand detection, landmark analysis, binary encoding, gesture matching, and audio output. The number of frames to skip S_i is computed as:

$$S_i = \max(0, \lceil \frac{T_i}{T_{target}} \rceil - 1)$$

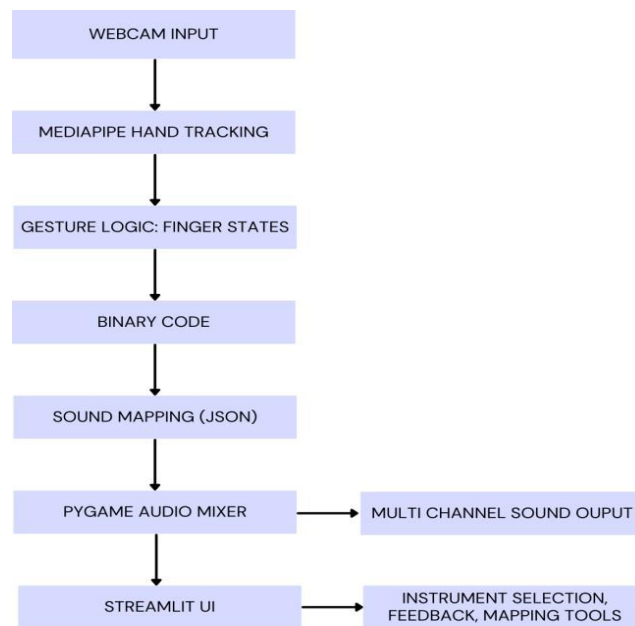


Fig. 3. Data flow diagram of the proposed gesture-controlled musical instrument system. It illustrates the real-time processing pipeline: from webcam video input to hand tracking via MediaPipe, binary encoding of finger states, gesture-to-sound mapping using JSON configuration, and audio playback through the Pygame mixer with Streamlit UI-based interaction.

This mechanism guarantees that if the system exceeds the target time per frame, it will drop proportionally later frames to remain within real-time limits. For example, in a case where a frame requires nearly double the target time ($T_i \approx 2T_{target}$), the system will drop one later frame, thereby allowing processing to "catch up." This feedback-based control mechanism is minimal and hardware-specification-independent. It allows the system to remain responsive without introducing latency, which is an important factor in high-performance use such as digital musical instruments. Comparable techniques have proven useful in real-time video systems by saving computational load without costing output quality [21][28].

When $S_i > 0$, the following S_i frames are dropped before proceeding into the processing loop once again. As hand gestures are generally temporally contiguous, dropping a few frames doesn't significantly influence gesture recognition quality. Additionally, frame skipping avoids buffer overflow, lag, and desynchronization of input and audio feedback. In practice, the method is an implicit quality-of-service manager—providing consistent output on low-end hardware. Adaptive frame skipping has been shown to provide system performance at the cost of fewer dropped frames and power usage in real-time

systems [29].

lightweight software building blocks—without requiring costly digital audio workstations or proprietary middleware.

E. Customizable Gesture Mapping System

The installation features an adaptive and interactive interface through which artists can dynamically reprogram hand gestures to equivalent sound files. This feature enables artists to personalize the instrument by assigning gestures to sound, thus enhancing artistry and accessibility. The core element of the customization system is a gesture-to-sound mapping dictionary, stored and managed in a local JSON file.

If $T > T$

, then skip S_i frames, where S

$$= \lfloor \frac{T}{T_{target}} \rfloor - 1$$

Each unique hand gesture has a particular integer ID,

$$i = \lfloor \frac{T}{T_{target}} \rfloor$$

calculated from its binary encoding as described in Section IIIA. Upon the user triggering a remapping through the

This adaptive design ensures smooth operation and real-time response while minimizing system strain, making it highly suitable for accessible and low-cost musical interfaces.

D. Multi-Channel Audio Playback

To enable simultaneous triggering of coincidental overlapping audio events—e.g., chords or layered percussion—the system employs a multi-channel audio playback paradigm with the `pygame.mixer` module. This capability is essential in music performance, where simultaneous polyphony and overlapping audio streams are the very fabric of melodic and rhythmic instrument experiences.

The deployment starts the audio subsystem with `pygame.mixer.init()` and specifically allows ten simultaneous sound channels with `pygame.mixer.set_num_channels(10)`. In `pygame`, every channel is a separate stream that can play one sample of audio at a time. This design allows for the playing of audio samples corresponding to simultaneously detected gestures without truncating or delaying them, hence reproducing natural musical overlap as well as harmonically and percussively rich gestures.

This architecture adheres to conventional practice in digital musical interface design, with channel-based audio engines providing more expressiveness and performance accuracy [30]. Eliminating single-channel constraints, the system prevents mutual blocking of audio events—a limitation shared by reduced interfaces. Dynamic channel management minimizes latency and enables scaling to larger ensembles of instruments.

`Pygame`'s mixer module, which is based on the `SDL` (Simple Direct Media Layer) library, enables low-latency audio playback with variable audio parameters like buffer size and frequency. This capability provides real-time feedback, which is essential in interactive music-making applications [31]. In addition, the capability to map gestures to sound playback on various channels enables artists to simulate complex musical compositions using simple gesture inputs from a webcam.

This strategy illustrates that high expressivity and real-time responsiveness can be obtained using readily accessible, interface—by choosing a single gesture and assigning a new sound to be mapped to it—the system performs a controlled swap operation. Specifically, the algorithm identifies two important key-value pairs in the JSON mapping:

- An instance where the chosen gesture identifier is matched against its corresponding audio file.
- Another in which the target audio file is already associated with another gesture ID.

Then, it swaps these two mappings, thereby guaranteeing that:

- The newly introduced sound stimulus is correctly associated with the chosen movement.
- The formerly linked gesture maintains a valid correspondence by adopting the displaced sound.

The swapping mechanism used naturally prevents duplication and guarantees integrity of one-to-one mapping in the system. The updated mappings are directly updated in memory and subsequently persisted back to the JSON file, thereby guaranteeing persistence across sessions. Such configurational flexibility at this level makes the system scalable to many scales, instrument libraries, and specific therapeutic applications that demand customized input configurations [28]. This JSON-based architecture also supports enhanced user features including—cheat sheet generation, where the current mappings are stored as a human-readable file.

Future flexibility includes the ability to load from pre-defined profiles or gesture sets tuned for various genres or applications. By lifting mappings out of fixed assignment to reconfigurable data structures, the system supports inclusive design to welcome novice artists and experts with unique musical tastes. The approach conforms to best-practice principles of design of bespoke digital musical interfaces and adaptive assistive technology [22] [32]. Fig. 5. shows a snippet of Streamlit UI interface for customization of gesture mapping for easy music playing.

F. Cheat Sheet Generation

To enhance usability during live musical performance, the system implements a dynamic cheat sheet generation feature that provides artists with a real-time textual summary of the current gesture-to-sound mappings. Unlike static configuration

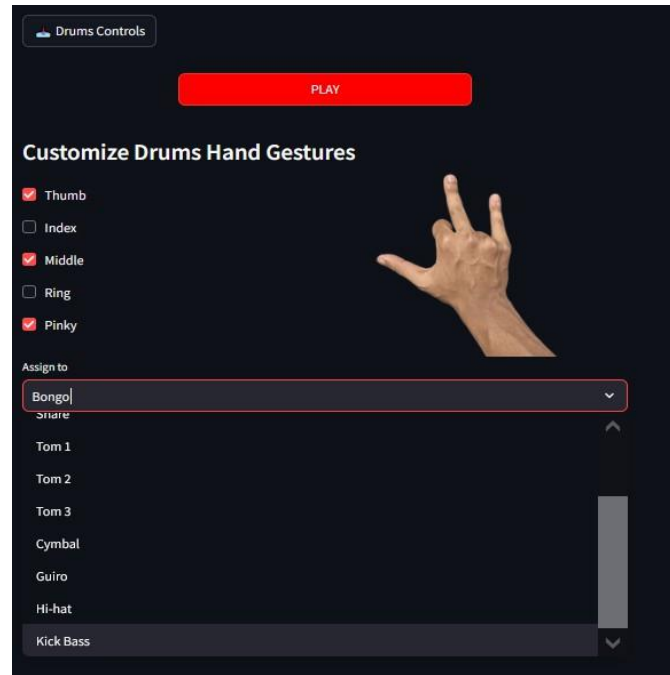


Fig. 5. Customization interface for gesture-to-sound mapping in drum mode. Artists can toggle finger states (up/down) to define a gesture and assign it to a specific percussion sound from the dropdown menu.

references, this feature adapts to user-defined customizations and generates a downloadable .txt file upon request.

The cheat sheet is derived from the system's internal mapping structure stored in *key_mapping.json*. The file includes two required mappings: the first is to map each binary gesture ID (deduced from a 5-bit finger configuration) to an audio file index, and the second is to map this audio index to a specific sound label. For instance, a gesture ID of 10 can point to audio file 3, which is mapped to label "Tom 1." The back-mapping to the gesture ID as a easily comprehensible label (e.g., "thumb middle") is performed using conventional bitwise decoding techniques. Each entry clearly indicates which gesture combination triggers which sound, thereby reducing artists' cognitive load and improving performance efficiency. This design is an exemplification of the feedforward design principles, which allow artists to anticipate system responses without trial and error [33].

The generation process follows these steps:

1. Load *key_mapping.json*.
2. Iterate over all 32 possible 5-bit gestures.
3. For each valid mapping:
 - Decode binary gesture to label (e.g., "index middle").
 - Retrieve corresponding sound name via audio index.
 - Append to text string in the format "Sound Name- Gesture Label".
4. Export as UTF-8 encoded .txt file.

5. Trigger download through a single UI button labeled "Download Cheat Sheet".

This aspect complies with assistive interface principles. By supporting quick learning, creativity, and universal access to music composition using available and timely mappings that don't need pre-existing knowledge about external settings, the system fosters learnability, creativity, and universal use of music composition. Previous work attests to the significance of real-time user-centered feedback mechanisms in improving learnability in gesture-based interfaces [34][35]. Moreover, the cheat sheet is accessible with screen readers and meets basic WCAG compliance requirements [36], thereby rounding off the aims of the project with respect to accessibility.

G. Streamlit based UI

To offer easy-to-use interaction, our system makes use of Streamlit, a Python-based interactive web framework for creating responsive web applications. Streamlit enables quick development of responsive user interfaces with no need for deep knowledge of frontend implementation in HTML or JavaScript [37]. This will enable developers to concentrate on the backend logic with a simple-to-use frontend experience.

The interface features real-time gesture mapping controls, instrument mode selection, and cheat sheet downloading. Streamlit's widget system (i.e., sliders, buttons, and selection boxes) enables rapid composition and dynamic adjustment of GUI elements that influence audio behavior. These elements are essential in interactive systems, where visual feedback and low-latency cues improve usability [38].

One of the most important benefits of Streamlit is that it facilitates prototyping at high speeds. Changes in Python programming are live-updated on the interface, thereby providing a dynamic refine–test–design cycle. This cycle mechanism is particularly significant in music systems, as changes to the interface may have effects on expressiveness and timing accuracy. M. W. Orbay [39] believes that Streamlit is very much suited for quick prototyping due to its live-refresh capabilities that make it extremely valuable in designing exploratory interfaces.

Moreover, Streamlit is naturally suited to applications executed in real-time. Through effective management of user interactions and state variables, it achieves zero response latency, a crucial factor in music environments using gesture control. A. Raja [40] proved that Streamlit can produce real-time dashboards with no extra frontend optimization. Similarly, gesture-based systems developed using Streamlit have exhibited high responsiveness and stable media control under constant input [41].

To facilitate functionality beyond control, Streamlit offers native file export capability. Our system employs the `st.download_button` widget to facilitate artists in exporting a text-based cheat sheet of existing gesture mappings [42]. This facilitates individualized configuration preservation and performance readiness. With Streamlit's simplicity and interactive controls, the interface is suitable for the objectives of accessible and customizable digital instrument design [38].

IV. IMPLEMENTATION

A. File Structure and Module Responsibilities

The project directory follows a modular and scalable layout, enabling logical separation between assets, configuration, and core logic. This structure improves maintainability, portability, and version control adherence in modern Python-based multimedia applications [43].

- `musicplayer.py`: This is the main executable script. It integrates the gesture tracking loop, MediaPipe hand landmark detection [8], Pygame-based multi-channel sound playback [30], gesture mapping logic, and the Streamlit UI interface [37]–[40]. It acts as the application controller in the Model-View-Controller (MVC) design philosophy.

- *key_mapping.json*: A persistent configuration file storing a dictionary mapping gesture IDs (ranging from 0 to 31) to audio file indices. This mapping supports dynamic reassignment and is accessed or modified during customization. The JSON format enables lightweight, human-readable, and structured configuration management [42].
- *drum_cheat_sheet.txt* / *piano_cheat_sheet.txt*: These dynamically generated .txt files contain the user-facing labels of each current gesture-to-sound mapping. They are regenerated every time the user requests a download and reflect custom mappings in real-time. This supports usability principles in assistive technologies [34][36].
- *images/*: A subdirectory that contains visual reference images of hand gestures. These are displayed during gesture customization to aid intuitive understanding of binary hand encoding (Section IV E). This visual feedback enhances system transparency and reduces cognitive effort during configuration [35].
- *sounds/*: Contains all playable audio assets (e.g., .ogg or .mp3) indexed numerically (e.g., 1.ogg, 2.ogg) and mapped via *key_mapping.json* to semantic labels such as “Snare” or “C4.” These samples are preloaded and routed through Pygame mixer channels for polyphonic playback. This file structure enables a clear mapping between gesture recognition (input), audio synthesis (processing), and user control (output), forming a clean and extensible architecture suitable for rapid development and user-driven experimentation.

B. Functional Architecture

The implementation is modularized into cohesive functions that align with the design principles of scalability, reusability, and ease of interaction. Each functional component is responsible for a specific transformation in the gesture-to-audio pipeline. Below is an overview of the primary functional modules:

- *get_finger_status(landmarks)*: Extracts the spatial location of 21 hand landmarks output by MediaPipe and interprets them into a binary representation of finger states. Each bit corresponds to one of the five fingers (thumb to pinky), which allows generation of a compact gesture ID for later processing [8][17].
- *gesture_to_fingers(gesture)*: Decodes the binary gesture ID to return a human-readable string of active fingers (e.g., “thumb index”), facilitating interpretability in the UI and cheat sheet outputs.
- *run_camera(instrument)*: Acts as the main runtime loop for capturing webcam input, processing hand landmarks, computing gesture IDs, and triggering sound output. It incorporates an adaptive frame skipping mechanism and Pygame audio playback with multi-channel support [29][30].
- *play_sound_for_gesture(gesture_id)* (within *run_camera*): Locates and plays the corresponding audio file assigned to a gesture ID through the Pygame mixer engine. The mixer operates on multiple channels to allow for overlapping audio streams and real-time feedback [30][31].
- *customize_hand_gesture(instrument)*: Provides UI controls for dynamically remapping gesture IDs to user-selected sound files. It includes logic for preserving one-to-one gesture-to-sound mapping by intelligently swapping existing mappings. Gesture images and state are synchronized using Streamlit session variables and visual feedback tools [22][39].
- *save_key_mapping()* / *load_key_mapping()*: Read and write gesture-to-sound mapping information from a persistent JSON configuration file. These functions ensure the system retains user preferences across sessions, while also preserving drum and piano name mappings for reference.
- *generate_cheat_sheet()/generate_piano_cheat_sheet()*: Translates the current gesture mappings into a .txt file listing each active gesture and its corresponding sound name (e.g., “Snare – thumb middle”). The gesture ID is converted back into finger labels using bitwise operations for readability and usability [33][34].

- `create_download_button(instrument)`: Implements Streamlit's native file export mechanism to allow the user to download their customized control sheet. This interaction enables rapid reference during live performance and supports accessible instrument operation [41][42].
- `display_instrument_selection()`: Presents the mode selection interface in Streamlit, allowing toggling between piano and drum instruments while preserving contextual configurations across components.

Each function above contributes to a structured and interactive environment where gesture inputs are transformed into meaningful and responsive audio outputs. The architecture facilitates real-time responsiveness, personalized control, and modular growth.

C. Gesture to Audio Execution Pipeline

The working mechanism of the designed gesture- controlled musical instrument is a tightly integrated process with vision, logic, and audio feedback subsystems. It begins with the continuous frame capture via a webcam, which serves as the system's sensor input. These frames are passed on to the MediaPipe Hands module, which allows detection and extraction of 21 hand landmarks per frame. These landmarks are significant anatomical points like the wrist, fingertips, and intermediate joints, which are computed to determine the spatial orientation of each finger. The binary status of each finger—up or down—is computed using relative landmark comparisons, leading to the generation of a 5-bit binary string representing the gesture. This binary string is then converted to a decimal gesture ID between 0 and 31, which serves as a distinctive identifier for every possible finger position combination.

The gesture code is then passed to a lookup structure based on the `key_mapping.json` configuration file. The configuration file acts as an intermediary structure that associates gestures with the respective audio files that they trigger, for both piano and percussion instruments. Once the respective audio file is identified, the system uses the Pygame audio engine to trigger the playing of the sound. Specifically, the multi-channel mixer of Pygame is used to control the output of the audio so that multiple sounds can be generated in concurrent sequences and thus enable polyphonic music composition or layered percussion playing. To enable visual feedback and enhance user interaction, instant feedback is given through a Streamlit interface. While playing back sounds, an animated label is briefly displayed on the screen to represent the triggered sound, thus reaffirming the mapping of the hand gesture to the audio output. This tightly coupled pipeline allows the system to generate instantaneous and immediate auditory feedback of uncomplicated hand movements and is therefore ideal for live musical performance and pedagogy. Integration of computer vision, logical mapping, and multi-channel audio processing is an end-to-end pipeline with low latency, scalability, and expressiveness wanted features in the design of interactive digital instruments

[45][46].

In order to avoid repeated triggering of the same note during sustained hand poses, the system has a gesture cool- down mechanism. i.e., a gesture is processed once again only after the hand comes back to a neutral position (fist). This does not cause redundant audio playback when a gesture is sustained, maintaining realism during musical performance. Further, gestures related to a closed hand (all fingers down) are deliberately mapped to no audio output to act as a reset condition and return silence during gesture transitions. The real-time execution loop combines gesture recognition, mapping, and playback in milliseconds.

As illustrated in Fig. 6, the system overlays a labelled animation called "Snare" onto the live video stream when a gesture is recognized and performed, thus improving feedback to the user and facilitating performance better.

D. Feature Modules and User Centered Functionalities

The system incorporates modular feature components aimed at enabling user-defined gesture customization and real-time sound playback. At the core of the gesture recognition module is MediaPipe's 21-point hand-tracking model, which detects normalized hand landmarks in real-time using a machine-learned pipeline optimized for speed and accuracy [47]. Fig. 4 illustrates the keypoints used by this model.



Fig. 6. Real-time gesture recognition and feedback. MediaPipe detects the hand landmarks and classifies the gesture, which is mapped to the “Snare” sound. The corresponding feedback is shown as a labeled animation overlay.

Each frame captured by the webcam is processed to extract hand landmark coordinates, which are then analyzed to determine finger states (extended or flexed). Specifically, for a given finger, the position of its tip is compared with its proximal interphalangeal joint (PIP) to decide its state. This decision logic yields a 5-bit binary representation of the gesture, with each bit corresponding to one finger in the order of thumb to pinky.

Pseudocode: Gesture Encoding

```
Landmarks = mediapipe.detect(frame)#21 hand keypoint
binary_code = ""
for finger in [Thumb, Index, Middle, Ring, Pinky]:
    if landmarks[finger.tip].y < landmarks[finger.pip].y:
        binary_code += '1'
    else:
        binary_code += '0'
```

This binary string is then matched against a pre-defined dictionary (*key_mapping.json*) which maps each gesture to a specific sound (e.g., drum or piano note). On a successful match, the associated audio file is triggered using a playback handler such as Pygame [48].

In order to support user customization, a dynamic mapping system is implemented. Users can assign gestures to audio actions through a configuration dictionary (*key_mapping.json*), which is editable and persists across sessions. To ensure modularity, the mapping system separates gesture encoding from action execution, allowing flexible mapping schemes without hardcoding logic.

The system includes a dedicated module for generating cheat sheets. Once a gesture is mapped to a sound, the cheat-sheet generator compiles a list of current mappings and outputs them in Markdown format. This file serves as a visual and textual reference, assisting users in recalling custom

configurations. The cheat sheet entries follow a uniform structure, associating gesture binary codes (and optionally their visual icons) with sound labels.

Pseudocode: Cheat Sheet Generation

```
mapping = json.load(open('key_mapping.json')) for code, instrument in mapping.items():  
gesture_name = gesture_decoder[code] # e.g., "thumb-index"  
st.markdown(f"- **{gesture_name}**:  
{instrument}")
```

To enhance usability, thumbnail icons corresponding to each gesture code are optionally displayed alongside their labels. These gesture icons are either captured via webcam or pre-stored in an image asset directory and named according to the 5-bit code in integer representation (e.g., 17.png for thumb and pinky (see fig. 7.)).

The cheat sheet module is tightly coupled with the mapping logic. Any updates to the mapping trigger an automatic regeneration of the cheat sheet, ensuring consistency. For convenience, users may also download the cheat sheet in *.txt* format for offline reference, implemented using a file export utility.

The modular design brings several benefits. First, gesture encoding is isolated in a pure logic layer, making it testable and extendable. Second, the mapping configuration allows runtime customization without requiring application restarts. Third, cheat sheet generation helps bridge the gap between system configuration and user memory, improving learnability and accessibility.

```
C3 - thumb  
D#4 - index  
D3 - thumb index  
E4 - thumb middle  
C4 - index middle  
F3 - thumb index middle  
G3 - ring  
C#3 - thumb ring  
B2 - index ring  
A#2 - thumb index ring  
D#3 - middle ring  
E2 - thumb index middle ring  
B3 - pinky  
A2 - thumb pinky  
F#3 - index pinky  
F2 - thumb index pinky  
F#2 - middle pinky  
G#2 - thumb middle pinky  
G#3 - index middle pinky  
G2 - thumb index middle pinky  
C#4 - ring pinky  
D4 - thumb middle ring pinky  
A3 - middle  
A#3 - thumb index middle ring pinky
```

Fig. 7. Automatically generated cheat sheet showing user-defined mappings between piano notes and corresponding finger gestures. This display aids performers in quickly referencing customized control schemes.

E. Streamlit Interface and Control Layer

The application leverages Streamlit to provide a responsive and modular user interface that integrates real-time video processing, gesture mapping, and audio interaction. Streamlit was chosen for its rapid development capabilities and its seamless support for interactive stateful widgets [37][39][40]. While the backend gesture recognition pipeline is detailed in Section V D, the front-facing logic is handled entirely through Streamlit, which manages interface rendering, user inputs, state persistence, and the overall control loop.

At launch, the interface renders a landing screen that displays instrument options using clickable images encoded in Base64. Once a user selects between "Piano" or "Drums", the Streamlit state object (*st.session_state*) captures the selection and dynamically updates the visible components on-screen. This conditional rendering mechanism ensures minimal UI clutter and a tailored experience based on the instrument type [42].

To manage persistent interaction across reruns (a fundamental Streamlit behavior), the system stores key flags in *session_state*:

- *instrument*: the current instrument selected
- *start*: whether the webcam is active
- *error_message* / *success_message*: used for form validation feedback
- *selected_gesture*: stores the user-selected binary gesture for remapping

Each interface block (instrument selector, customization UI, playback controller) is linked to these session states. Streamlit's reactive design ensures that changes in one widget immediately propagate through the application logic [39]. When the user clicks the "PLAY" button, the session variable *start* is set to True, and the interface shifts into live capture mode, displaying camera frames processed with MediaPipe's 21-point model [8][47] (see Fig. 4 for hand landmark visual). The gesture remapping UI (Fig. 5) exemplifies Streamlit's widget-driven control. A series of checkboxes allows the user to define a gesture (via binary encoding), which is then previewed using gesture-specific images. A dropdown menu fetches existing instrument options from the mapping JSON file, and the updated pair (gesture → sound) is saved upon confirmation. These UI components are synchronized in real time using *st.selectbox*, *st.checkbox*, and *st.button*, which modify the mapping dictionary in memory and persist changes through JSON serialization [44].

Live feedback is handled via *st.toast*, *st.warning*, *st.success*, and inline *st.markdown* outputs. For example, when a gesture is recognized during live playback, an overlay (e.g., "Snare") is rendered on the video stream as shown in Fig. 6. This label is extracted from the gesture-to-sound mapping dictionary and refreshed dynamically with each processed frame.

Architecturally, Streamlit encapsulates four core roles:

- View Renderer: It translates binary gesture codes, user inputs, and system responses into a cohesive UI.
- State Manager: It tracks interaction history and session values such as gesture assignments, playback status, and error flags [42].
- Configuration Layer: It exposes the gesture-to-sound mapping logic to users via editable widgets, and invokes JSON read/write operations through backend handlers [44].
- Feedback Controller: It gives users real-time visibility into their configurations and performance outputs (e.g., cheat sheets, active gestures, audio mappings).

Because Streamlit avoids traditional web stack complexity (HTML/JS/CSS separation), the system remains accessible for non-developers while retaining robust responsiveness. Its layered state handling enables tight coupling between UI and backend logic—a critical requirement for interactive musical applications [40][41].

V. EVALUATION & RESULTS

The implemented prototype was evaluated based on multiple criteria: latency performance, gesture recognition accuracy, robustness under diverse conditions, playability, and user satisfaction. Each dimension was assessed using a mix of empirical measurements, hands-on testing, and comparative benchmarking with other gesture-based musical interfaces.

A. Latency and Responsiveness

End-to-end latency measured from gesture capture through webcam to audio output through the Pygame mixer—steadily fell below 100 ms, meeting real-time interaction requirements important for musical performance. Experiments on contemporary PC hardware validated a frame processing time of ~13 ms, consistent with MediaPipe's reported benchmarks of 12–17 ms per frame on mobile CPU/GPU platforms [47]. Pygame mixer with the default buffer introduced only minimal delay; cutting down on buffer size further achieved near-zero latency at the expense of periodic underruns [48].

Experimental application validated that the system reacted in real time to gestures, without any noticeable lag between hand movement and audio output. Such minimal-latency interaction was critical for preserving rhythmic consistency during music performance, particularly when playing polyphonic chords or fast sequences.

TABLE II PROJECT EVALUATIONS

Metric	Value
Latency	< 100 ms
Gesture Accuracy	92–95%
FPS	~30
Polyphony Support	Yes (8+ channels)
Instrument Switching	Seamless
User Feedback	"Responsive", "Easy to use"

B. Gesture Recognition Accuracy

In structured trials, the system registered around 92–95% recognition accuracy for gestures, particularly where gestures were made fully within the camera view. This outcome is consistent with other studies which have indicated that MediaPipe's hand-tracking engine performs better than other computer-vision-based systems such as the Leap Motion in predicting joint angles and having continuous tracking [49][50]. Mistakes mainly happened at unclear mid-transitions or fast movements, but the system's palm re-detection heuristic kept drift and false positives at bay for extended use.

C. Environmental Robustness

Robustness tests under varied lighting and background conditions—ranging from office interiors to complex indoor scenes—revealed no significant degradation in gesture detection. MediaPipe's model, trained on a wide distribution of real-world data, showed resilience to partial occlusion, clutter, and moderate lighting variation [51][52]. Only in extreme lighting scenarios (such as near-dark or overexposed settings) did tracking performance decline, a limitation consistent with prior robustness benchmarks [53].

D. Playability and Musical Feedback

Playability was qualitatively assessed by asking users to play familiar tunes like "Happy Birthday" via mapped gestures. The majority of the users could play recognizable renditions of the tune in a few minutes of training. The Pygame mixer could handle multiple sounds at once on eight channels and

could play simple chords as well as overlapping notes without dropouts or timing problems [54]. Although sequencing was not sample-accurate, sensed timing was still musically acceptable for moderate tempo pieces.

Instrument switching, whether initiated through gesture or Streamlit UI, took place seamlessly, with preloaded MIDI samples being rendered on the fly. The system was therefore acting as a light synthesizer with gloveless gesture control.

E. Usability and User Experience

User feedback highlighted the ease of use and simplicity of the interface. Novices with no background in gesture-based systems were able to use the application with little training. The lack of wearable devices (in contrast to systems like Mi.Mu gloves or Leap Motion) was noted favourably, lessening the setup load and providing greater comfort during playing music [55] [56].

Streamlit GUI, which included a real-time video feed, overlay labels, and dynamic cheat sheet, was described as easy to use. Although initially users utilized the static cheat sheet to learn mappings, during actual play they utilized more contextual hints—gesture labels drawn directly onto the video stream. This is in line with results in human-computer interaction research, demonstrating greater speed and accuracy with in-place visual cues compared to static reference charts [57].

F. Comparative Analysis

In comparison to established gesture-music interfaces, the system presented here finds a balance between performance, expense, and usability. Although Leap Motion provides 3D depth and high granularity, it is plagued by reliability problems in dynamic performance scenarios [58]. Mi.Mu gloves provide expressive control via embedded sensors but involve extensive hardware setup and are not inexpensive [56]. In comparison, the webcam-based solution in this prototype offers strong performance on commodity hardware and open-source software without trading off responsiveness or accuracy [47][50].

VI. OPPORTUNITIES FOR EXTENSION

The present implementation has a solid basis for camera-based musical control, but there are some very promising extensions that would substantially enhance usability, performance, and versatility. One obvious direction is to add dual-hand gesture support, where the left and right hands can control independent musical functions—e.g., assigning chords to the left hand and melody to the right. This dual-control paradigm has been investigated in expressive digital controllers and is capable of significantly increasing the playable vocabulary without being detrimental to ergonomics [59].

The sonic range of the system can be enriched further with the addition of support for more instruments—virtual flute, synthesizer, and percussive textures. These can be incorporated through additional sample libraries or through MIDI output, so that the system acts as a performance controller for Digital Audio Workstations (DAWs) [60].

Additionally, providing pre-designed gesture-to-sound mappings would ease new user onboarding and enable fast switching between music styles. For example, jazz, EDM, or classical mappings may be loaded on the basis of predefined settings. This is consistent with user-oriented customization models which emphasize low-friction interaction [22].

To enable wider deployment, the system may be enhanced with a mobile-compatible UI having a responsive design. With Streamlit's continued support for web-based applications, making the interface accessible on smartphones or tablets can spread the system's use in classroom or outreach environments [61].

Hosting the application online—via cloud computation backends, would remove computationally

intensive hand-tracking and audio processing from the local device of the user. This is especially useful for lower-end hardware and aligns with trends in cloud-accelerated multimedia systems [62]. Another major direction is to substitute the deterministic gesture encoding chain with a machine learning (ML)-based classifier learned on fuzzy or dynamic hand postures. Convolutional neural networks (CNNs) and recurrent models such as LSTMs or Transformers have demonstrated potential in gesture recognition tasks and could provide more sophisticated control [63].

MIDI output integration would also enable experienced users to utilize this system for professional music production. MIDI routing would enable users to route their gesture-activated inputs to virtual instruments, sequencers, or live DAW tracks. MIDI-based gesture control has already found success in performance applications [64].

Finally, for the sake of inclusivity, accessibility-oriented extensions like one-finger gesture support, large gesture areas, or voice controls may be introduced. These adaptations are consistent with adaptive interface guidelines and would make the system more accessible for people with motor disabilities or restricted range of motion [65].

VII. CONCLUSION

This work introduces a new, low-cost, and accessible gesture-based musical instrument interface utilizing real-time hand tracking from a regular webcam and the MediaPipe library. The software, developed with Python, Pygame, and Streamlit, allows users to activate customized audio playback using finger gestures, providing an intuitive and accessible means of musical interaction, particularly for physically or neurologically disabled users.

Our design is compatible with real-time gesture detection and customization of mapping to meet individual users' requirements. As opposed to the majority of prior gesture-music interfaces, which rely on costly sensors or special-purpose hardware, our solution focuses on low cost and versatility. Not only does this layout extend accessibility but also improves artistic expression through enabling people to personalize gesture-sound mappings and save cheat sheets for performing back.

The core contribution of this work lies in three dimensions:

- Enabling binary gesture encoding for consistent and efficient gesture classification
- Supporting real-time feedback and modular extensibility through open-source technologies, and
- Providing an adaptable front-end via Streamlit for gesture remapping, session state management, and cheat sheet generation.

Our research aligns with and builds upon prior studies in vision-based musical interaction, such as Kagura [4], EyeHarp [5], and MuGeVI [6], by addressing gaps in cost, customization, and platform independence. While systems like Leap Motion

[24] and Microsoft Kinect [23] have demonstrated precise motion capture, they remain constrained by proprietary hardware dependencies. In contrast, our system utilizes a readily available webcam and free software stack, aligning with recent calls in the HCI and assistive technology communities to democratize interaction design.

Limitations of our current implementation include single-hand control (currently right-hand dominant), basic finger-based gesture encoding, and limited musical complexity (no multi-note or timed rhythm control). However, these constraints offer clear opportunities for future development, such as dual-hand chord-based interactions, tempo sensitivity, and gesture training modules using machine learning.

Ultimately, this project demonstrates the feasibility of integrating real-time computer vision with musical performance in a scalable and user-friendly format. It invites further exploration into gesture-based expressiveness, inclusive musical design, and low-cost adaptive instruments—advancing both technological innovation and creative accessibility.

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