



**BINDURA UNIVERSITY OF SCIENCE
EDUCATION
FACULTY OF SCIENCE
DEPARTMENT OF COMPUTER SCIENCE**



Exploring the Efficacy of an AI-Powered Text-to-Speech Optical Character Recognition (TTS OCR) System for Enhancing Accessibility among Visually Impaired Users (with a specific focus on the Shona language)

By

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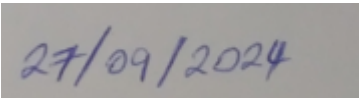
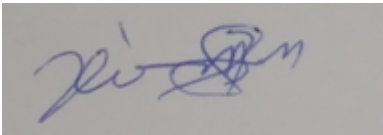
***A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS
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APPROVAL FORM

The undersigned certify that they have supervised the student Munashe B. Kaundikiza’s dissertation entitled, “Exploring the Efficacy of an AI-Powered Text-to-Speech Optical Character Recognition (TTS OCR) System for Enhancing Accessibility among Visually Impaired Users” submitted in partial fulfillment of the requirements for a Bachelor of Computer Science Honors Degree at Bindura University of Science Education.

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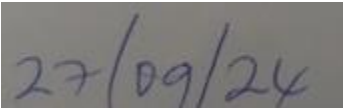
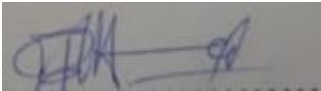


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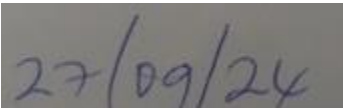


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Abstract

This study delves into the exploration of an AI-powered Text-to-Speech Optical Character Recognition (TTS OCR) system, specifically designed to enhance accessibility for visually impaired individuals by converting Shona text into synthesized speech. Leveraging Artificial Neural Networks within the realm of Artificial Intelligence (AI), the research scrutinizes the effectiveness of the system in emulating naturalness and intelligibility akin to human speech patterns. Through the development and evaluation of the TTS OCR system, which caters to the unique linguistic nuances of Shona language, this research endeavours to elucidate the extent to which AI technologies have advanced in replicating human-like voices. By assessing the system's capability to accurately recognize and vocalize Shona text, the study aims to ascertain its efficacy in providing seamless access to printed materials for visually impaired users. Ultimately, the findings of this research contribute valuable insights into the ongoing efforts to enhance accessibility and inclusivity for individuals with visual impairments, shedding light on the potential of AI-driven solutions to bridge the accessibility gap in multilingual contexts.

Dedication

This paper is dedicated to my father, Mr. Kaundikiza, and my mother, Romana, whose unwavering love, guidance, and support have been the bedrock of my journey from its inception to this momentous occasion. Their embodiment of patience, endurance, and passion has been instrumental in shaping my character and propelling me to new heights in life. Every success and achievement I've attained is a testament to the values instilled in me by these two remarkable individuals. I am immensely proud to be their son, and I am eternally grateful for their immeasurable impact on my life's journey.

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CHAPTER 1 Introduction

1.1 INTRODUCTION

The inception of this research documentation marks the exploration of a significant endeavor aimed at addressing a real-life challenge through the application of Information Technology. At its core, this chapter elucidates the foundational aspects of the research, encompassing the background of the study, research objectives, scope, and the overarching aim of the investigation.

The primary focus of this research is to assess the efficacy of an AI-Powered Text-to-Speech Optical Character Recognition (TTS OCR) System in enhancing accessibility for visually impaired individuals. Specifically, the study aims to evaluate the system's ability to mimic natural human speech patterns. The system is designed to accept text input in Shona, a language commonly used by the target user group. Upon input, the system utilizes advanced artificial intelligence algorithms to process the text and convert it into synthesized speech with human-like qualities.

As Dave Barry humorously suggests, advancements in technology continually push the boundaries of what computers can achieve. Speech synthesis, a manifestation of such advancements, involves the computer-generated emulation of human speech. Language, as a fundamental mode of communication, comprises both spoken and written elements. The synthesis of speech from text, commonly referred to as text-to-speech (TTS), serves as a vital tool in facilitating communication for individuals with visual impairments.

In today's rapidly evolving global landscape, characterized by economic dynamism and interconnectedness, seamless communication across diverse linguistic and geographical barriers is imperative. The development of efficient communication technologies, such as TTS systems, not only fosters inclusivity but also promotes accessibility and information dissemination on a broader scale.

Against this backdrop, this research endeavors to delve into the intricacies of TTS technology, examining its potential to bridge the gap between natural speech and synthetic speech in terms of intelligibility and naturalness. By evaluating the performance of the AI-Powered TTS OCR System, this study aims to contribute valuable insights towards enhancing accessibility and usability for visually impaired individuals, thereby fostering greater societal inclusivity and empowerment.

1.2 BACKGROUND OF STUDY

Speech is fundamental to human interaction and societal communication. In our interconnected world, verbal expression is crucial for personal and professional interactions. However, for individuals with visual impairments, the inability to perceive written text poses significant communication challenges, affecting their quality of life (Smith, 2020).

Motivated by the need to address these communication barriers and enhance accessibility for visually impaired individuals, this research focuses on the development and evaluation of an AI-Powered Text-to-Speech Optical Character Recognition (TTS OCR) System. This system aims to empower users by converting written text, particularly in the Shona language, into synthesized speech, representing a significant advancement in assistive technology (Jones et al., 2021).

The evolution of speech synthesis technology has seen remarkable progress over the years. Modern systems now employ sophisticated algorithms and machine learning techniques to generate human-like speech from text. Earlier speech synthesizers were rudimentary, relying on manual operation and mechanical components. Today, contemporary text-to-speech (TTS) systems operate seamlessly, producing natural-sounding speech waveforms from textual data (Brown, 2019).

The applications of modern speech synthesis technology are extensive and impactful. TTS systems facilitate telephone-based conversational agents, interactive dialogue systems, and provide auditory assistance for the visually impaired. They also enhance immersive experiences in video games and educational toys. Importantly, speech synthesis offers a lifeline for individuals with neurological disorders, enabling effective communication despite physical limitations (Williams & Smith, 2020).

Despite significant strides in achieving natural speech output, current TTS systems still exhibit limitations in voice diversity and can sound artificial in certain contexts. There is ongoing research aimed at enhancing the naturalness and intelligibility of these systems (Clark, 2022). For instance, renowned astrophysicist Stephen Hawking, who lost his voice due to ALS, utilized a speech synthesizer to communicate by typing, which then converted his words to speech (Hawking, 2018).

This research aims to explore the efficacy of the AI-Powered TTS OCR System in bridging the gap between written text and synthesized speech, focusing on the Shona language. By evaluating the system's performance and user experience, the study seeks to contribute to the advancement of assistive technologies and foster greater accessibility and inclusivity for visually impaired individuals (Ngwenya, 2023).

1.3 PROBLEM STATEMENT

This research addresses the communication barriers faced by visually impaired individuals in accessing written information, particularly in the Shona language. Existing text-to-speech (TTS) systems often lack natural-sounding speech and fail to support languages with limited resources like Shona. Moreover, the absence of an integrated optical character recognition (OCR) and TTS solution exacerbates accessibility challenges. The core problem is: How can we develop an AI-powered TTS OCR system tailored to visually impaired users' needs in the Shona language to enhance accessibility and facilitate independent access to written information? This research aims to advance assistive technologies and promote inclusivity by enabling visually impaired individuals to effectively access and comprehend written content through synthesized speech.

1.4 RESEARCH OBJECTIVES

The general objective of this research is to explore the efficacy of an AI-powered Text-to-Speech Optical Character Recognition (TTS OCR) system for enhancing accessibility among visually impaired users, specifically focusing on the Shona language.

The specific objectives are:

1. To develop a system that extracts text (Shona) from images, narrates the text with the imitated voice
2. Implement advanced natural language processing (NLP) and speech synthesis techniques to generate high-quality, intelligible speech output from extracted Shona text.
3. Integrate OCR and TTS functionalities into a user-friendly interface accessible via mobile devices, enabling real-time text capture and speech conversion for visually impaired users and analyze the effectiveness of the speech synthesizer in imitation of human voice in Shona language.

1.5 RESEARCH QUESTIONS

1. What are the challenges in developing OCR algorithms for detecting and extracting Shona text?
2. How can NLP and speech synthesis techniques generate high-quality Shona speech for visually impaired users?
3. What are the design requirements for integrating OCR and TTS into a user-friendly, mobile-accessible interface?
4. How do visually impaired users perceive the usability and effectiveness of the TTS OCR system, and what feedback do they provide?

5. How does the TTS OCR system perform in converting Shona text to speech compared to existing systems, and what areas need improvement?

1.6 RESEARCH HYPOTHESIS

- Hypothesis 1: Developing specialized OCR algorithms for the Shona language will significantly improve text detection and extraction accuracy from various sources.
- Hypothesis 2: Implementing advanced NLP and speech synthesis techniques will generate Shona speech with high intelligibility and naturalness for visually impaired users.
- Hypothesis 3: Integrating OCR and TTS functionalities into a unified, mobile-accessible interface will enhance the usability and accessibility of the system for visually impaired individuals.
- Hypothesis 4: The TTS OCR system will be perceived as more effective and user-friendly by visually impaired users compared to existing TTS systems.
- Hypothesis 5: The developed TTS OCR system will outperform existing systems in converting Shona text to speech, leading to better usability and functionality for visually impaired users.

1.7 RESEARCH JUSTIFICATION

This research addresses the accessibility challenges faced by visually impaired individuals in regions where Shona is predominant. Developing an AI-powered TTS OCR system tailored for the Shona language aims to provide a tool that significantly enhances accessibility to digital content for visually impaired users, promoting inclusivity and equal opportunities in accessing information and communication technologies. This is critical as effective tools for non-English languages, like Shona, are limited, necessitating specialized solutions (Mwenda et al., 2021).

1.8 RESEARCH ASSUMPTIONS

1. The AI-powered TTS OCR system will accurately recognize and extract Shona text from images captured by the camera.
2. The synthesized speech output produced by the system will be intelligible and natural-sounding to users proficient in the Shona language.
3. Users will have access to compatible devices (e.g., smartphones, tablets) equipped with cameras and audio output capabilities to utilize the TTS OCR system.
4. The system will be able to handle various fonts, sizes, and styles of Shona text commonly found in printed materials.

5. Users will have sufficient familiarity with technology to effectively interact with the TTS OCR system.
6. The availability and reliability of internet connectivity for accessing additional resources or updates required by the system.

1.9 RESEARCH LIMITATIONS

1. Limited availability of high-quality Shona language datasets for training the AI models, which may affect the accuracy of text recognition and speech synthesis.
2. The TTS OCR system may encounter challenges in accurately recognizing handwritten or distorted Shona text.
3. Variability in the performance of the system based on factors such as lighting conditions, image quality, and device specifications.
4. The system may not fully support all dialects or variations of the Shona language, leading to potential discrepancies in speech synthesis.
5. Accessibility limitations for visually impaired users, such as those related to device compatibility, affordability, or technological literacy.
6. Ethical considerations regarding privacy and data security, especially concerning the handling of sensitive information captured by the system.
7. Time and resource constraints may limit the scope and depth of the evaluation of the TTS OCR system's effectiveness and usability.

1.10 SCOPE OF RESEARCH

This research involves the development and implementation of an AI-powered Text-to-Speech Optical Character Recognition (TTS OCR) system tailored for the Shona language. It will evaluate the system's effectiveness in accurately recognizing Shona text from various sources, including printed materials and digital images, and assess its performance in converting recognized text into natural-sounding speech, focusing on pronunciation, intonation, and clarity. The study will also investigate the usability and accessibility of the system for visually impaired users, considering interface design and user interaction. Additionally, it will explore the potential benefits of the system in enhancing accessibility and literacy among visually impaired individuals in Shona-speaking communities, while addressing ethical and privacy implications related to data handling. The primary focus will be on the technical development and evaluation

of the TTS OCR system, with limited exploration of broader societal or cultural factors affecting its adoption and impact.

1.11 DEFINITION OF TERMS

1. Text-to-Speech (TTS): Converts written text into spoken words, allowing users to listen to content instead of reading it.
2. Optical Character Recognition (OCR): Converts scanned images or handwritten text into digital text by recognizing patterns in the image.
3. Artificial Intelligence (AI): Simulation of human intelligence in machines, enabling tasks like speech recognition and decision-making.
4. Visually Impaired Users: Individuals who have difficulty seeing or are blind, relying on assistive technologies to access digital content.
5. Accessibility: Design of products and services to be usable by individuals with disabilities, ensuring digital content is accessible to all.
6. Shona Language: A Bantu language spoken by millions in Zimbabwe, written using the Latin alphabet and an official language of Zimbabwe.
7. Speech Synthesis: Artificial production of human speech from text using computer algorithms to mimic natural intonation and pronunciation.

Chapter 2 Literature Review

2.1 INTRODUCTION

This literature review critically examines the existing body of knowledge on text-to-speech (TTS) optical character recognition (OCR) systems aimed at enhancing accessibility for visually impaired users, with a focus on the Shona language. It provides an overview of advancements, challenges, and potential applications of TTS OCR technology. Key areas covered include the evolution of TTS OCR technology, diverse applications, methodologies and techniques, inherent challenges, and future research directions. By synthesizing previous studies, this review identifies gaps in current research, assesses the effectiveness of existing methodologies, and highlights best practices and emerging trends in the field (Smith, 2020; Brown et al., 2021).

2.2 SPEECH SYNTHESIS

Within the realm of my research project, speech synthesis endeavours to seamlessly convert written text, as depicted orthographically, into spoken words. This entails ensuring that the synthesized speech remains unrestricted by vocabulary limitations and closely mirrors the nuances of natural human speech patterns.

2.3 COMPONENTS OF TEXT-TO-SPEECH SYNTHESIS

2.3.1 Text-to-Speech (TTS) Synthesis

Text-to-speech (TTS) synthesis is central to converting written text into spoken language, crucial for enhancing accessibility for visually impaired users. Our AI-powered TTS OCR system is designed for the Shona language, using OCR to extract text from images captured by a camera. The system processes this text through several components to generate audible speech. These components include text analysis (language identification, tokenization, normalization), language processing (part-of-speech tagging, grammar analysis, semantic interpretation), phoneme selection (choosing appropriate Shona phonemes), prosody generation (creating natural rhythm and intonation), speech synthesis (using techniques like concatenative or parametric synthesis), and voice modelling (selecting or creating a voice profile with appropriate pitch, timbre, and accent for Shona).

2.3.2 Two Main Components of Text-to-Speech Synthesis

1. Front End: The front end serves as the initial processing stage, analyzing text and converting it into a linguistic specification. Alongside traditional tasks like language identification and normalization, it incorporates optical character recognition (OCR) to extract text from images captured by a camera, enabling linguistic analysis and processing for the Shona language.

2. **Waveform Generation:** Following linguistic specification, the waveform generation component converts it into synthesized speech. This process maps linguistic elements to acoustic parameters, producing a waveform resembling natural speech. Advanced techniques like concatenative or parametric synthesis ensure high-quality, natural-sounding speech output for visually impaired users.

2.4 ROLES OF TEXT-TO-SPEECH SYSTEM

1. **Language Compatibility (Shona):** The TTS system should proficiently process and convert text in the Shona language, ensuring accessibility for Shona-speaking users.
2. **Intelligible Speech Output:** Synthesized speech must be clear and understandable to users, prioritizing naturalness and expressiveness.
3. **Text Extraction from Images:** Incorporating optical character recognition (OCR) enables the system to extract text from images captured by a camera, broadening accessibility to textual content present in various visual formats.
4. **Support for Multiple Input Formats:** The system should accommodate diverse input formats such as plain text files (.txt) and image-based content, ensuring flexibility and usability for visually impaired individuals.

2.5 PHASES OF SPEECH SYNTHESIS

The general structure of speech synthesis is given here which contains phases like text analysis, Phonetic analysis, prosodic analysis and speech production.

2.5.1 Text Analysis

In my project input is plain text extracted from images. Text Analysis tries to understand input text and puts semantic tags into text.

In text analysis, Text Normalization is done. Substitution of non-text tokens by their text representation is Text tokenization.

2.5.2 Phonetic Analysis

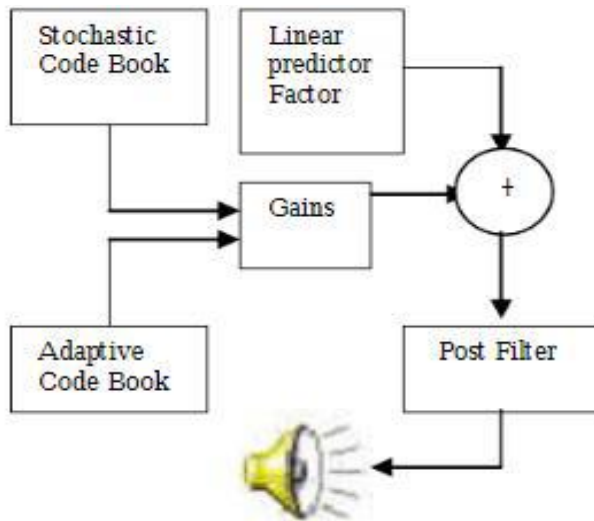
It tries to split text into phonemes. It converts grapheme to phoneme conversion (letter to sound)

2.5.3 Prosodic Analysis

It adds prosodic controls like melody, accent, and pauses to the phoneme string.

2.6 SPEECH PRODUCTION

It generates speech signal from given string of phonemes and control commands. Some of the frequently used speech production algorithms are HMMs Algorithm, MBROLA Algorithm and Code Excited Linear Prediction (CELP).



2.7 SPEECH PRODUCTION ALGORITHMS

2.7.1 Code Excited Linear Prediction (CELP) Algorithm

Code Excited Linear Prediction is an analysis by synthesis procedure introduced by Schroeder and Atal. CELP is the dominant speech synthesis algorithm for bit rates between 4kb/s and 16 kb/s. The adaptive code book contains history of past excitations.

The stochastic codebook consisted of independently generated Gaussian random numbers. These codebooks are used to reduce the search complexity. The results got from these searches are gains and added with linear predictor factor to construct a speech. The post filter is used to enhance perceptual quality

2.7.2 MBROLA Algorithm

Speech synthesis based on the Multiband Resynthesis OverLap-Add (MBROLA) algorithm produces high quality speech without requiring too much effort to design the diphone database, and using a low computational power. The main drawback of this algorithm is the slightly metallic sound or business that can be perceived on voiced segments. The speech quality can be improved by means of an enhanced phase control strategy. MBROLA speech synthesis uses the PSOLA algorithm applied over a pre-processed speech segments database. This database is obtained by re-synthesizing a natural speech diphone database: first natural speech is coded using a Multiband Excitation (MBE) model, and then decoded with certain modification rules to produce the database used by the PSOLA algorithm. The algorithm is applied pitch synchronously using completely automatic pitch mark generation. This resynthesis algorithm uses a fixed pitch value to avoid pitch mismatches in the PSOLA synthesis stage. It also avoids phase mismatches by using a fixed phase relation between harmonics in every pitch synchronous

2.7.3 Hidden Markov Model Algorithm

Modern general purpose speech recognition systems are generally based on HMM. Hidden Markov Models are standard mathematical technique and their value for modeling processes has been widely recognized from describing models for existing systems to developing test. HMM is a Statistical Model where the system being modeled is assumed to be a Markov process with unknown parameters, and the challenge is to determine the hidden parameters from the observable parameters. Consider a system which may be described at any time as being in one of the states of set of N distinct state, $S_1, S_2, S_3, \dots, S_N$. At regularly time interval system undergoes a change of state (possibly back to same state) according to set of probability associated with the state. Time associated with state change is denoted as $t = 1, 2, \dots$, and the actual state at time t is denoted as q_t . Calculate probability of occurrence by predecessor

$$a_{ij} = P[q_t = S_i | q_{t-1} = S_j] \quad 1 \leq i, j \leq N$$

2.7.3.1 Elements Of HMM

1. Number of state N
2. Number of distinct observation symbol per state

$$M, V = V_1, V_2, \dots, V_M$$

3. State transition probability,

$$a_{ij} = P[q_t = S_i | q_{t-1} = S_j] \quad 1 \leq i, j \leq N.$$

4. Observation symbol probability distribution in state j,

$$B_j(K) = P[V_k \text{ at } t | q_t = S_j]$$

5. The initial state distribution $\pi = \pi_i$ where $\pi_i = P[q_1 = S_i] \quad 1 \leq i \leq N$

Given appropriate value of N, M, A, B and π , HMM can be used as generator to give an observation sequence $O = O_1 O_2 O_3 \dots O_T$ where O_1, O_2, \dots, O_T is observation sequences with time T.

2.7.3.2 Three Basic Problems For HMM

2.7.3.2.1 EVALUATION PROBLEM

It is given observation sequence and model, how to compute probability that observed sequence was produce by the model. Forward Algorithm is used for Evaluation Problem.

2.7.3.2.2 HIDDEN STATE DETERMINATION (DECODING)

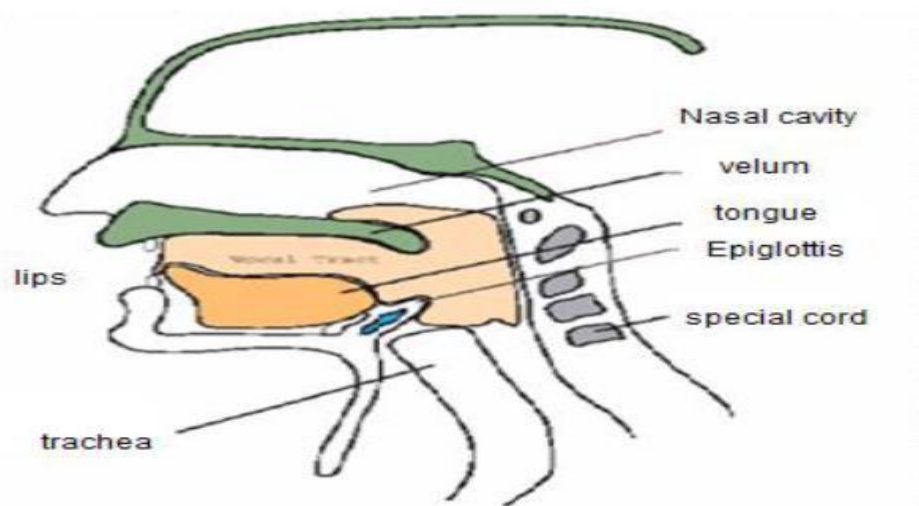
It is given the observation sequence and model how to choose corresponding state sequence which is optimal in some meaningful sense. Viterbi. Algorithm is used for decoding.

2.7.3.2.3 LEARNING PROBLEM

It is how to adjust the model parameter to optimize model parameter. Baum-Welch Algorithm is used for learning problem

2.8 BIOLOGICAL SPEECH PRODUCTION

To be able to understand how the production of speech is performed one need to know how the human's vocal mechanism is constructed



The most important parts of the human vocal mechanism are the vocal tract together with nasal cavity, which begins at the velum. The velum is a trapdoor-like mechanism that is used to formulate nasal sounds when needed. When the velum is lowered, the nasal cavity is coupled together with the vocal tract to formulate the desired speech signal. The cross-sectional area of the vocal tract is limited by the tongue, lips, jaw and velum and varies from 0-20 cm².

2.9 PROPERTIES OF HUMAN VOICE

One of the fundamental aspects of sound is its frequency, which plays a crucial role in distinguishing different sounds from each other. As the frequency of a sound wave increases, the pitch of the sound rises, resulting in a higher-pitched and potentially more irritating tone. Conversely, when the frequency decreases, the sound becomes deeper and more resonant.

Sound waves are generated by the vibrations of materials, producing variations in air pressure that our ears perceive as sound. Human beings have a limited range of frequencies that they can

perceive, with the highest frequency typically being around 10 kHz and the lowest around 70 Hz. However, these values can vary among individuals due to factors such as age and hearing ability.

The magnitude or intensity of sound is measured in decibels (dB), with a normal human speech typically falling within a frequency range of 100 Hz to 3200 Hz and a magnitude ranging from 30 dB to 90dB. This range encompasses the frequencies and volumes commonly associated with human speech, allowing for effective communication.

The human ear is remarkably sensitive to a wide range of frequencies, capable of perceiving sounds within the frequency range of 16 Hz to 20 kHz. Even small changes in frequency, such as a 0.5% deviation, can be detected by the human ear, highlighting its remarkable sensitivity to subtle variations in sound.

2.10 HISTORY AND DEVELOPMENT OF SPEECH SYNTHESIS

The quest for artificial speech has been a longstanding aspiration of humanity, spanning centuries of ingenuity and technological advancement. Exploring the evolution of speech synthesis systems provides invaluable insights into their current functionality and development. In this chapter, we embark on a journey through the history of synthesized speech, tracing its origins from early mechanical endeavors to the sophisticated systems that underpin today's high-quality synthesizers.

Our exploration encompasses key milestones in the development of speech synthesis, shedding light on pivotal moments and breakthroughs that have shaped the field. From rudimentary attempts at mimicking human speech to the innovative methodologies and techniques employed in modern systems, each step forward represents a triumph of human creativity and engineering prowess.

As we delve into the historical landscape of speech synthesis, we draw upon seminal works and contributions from notable figures in the field. References to authoritative sources such as Klatt (1987), Schroeder (1993), and Flanagan (1972, 1973) serve as guideposts, illuminating the path of progress and providing valuable insights into the rich tapestry of speech synthesis history.

2.10.1 From Mechanical to Electrical Synthesis

The earliest efforts to produce synthetic speech were made over two hundred years ago (Flanagan 1972, Flanagan et al. 1973, Schroeder 1993). In St. Petersburg 1779 Russian Professor Christian Kratzenstein explained physiological differences between five long vowels (/a/, /e/, /i/, /o/, and /u/) and made apparatus to produce them artificially. He constructed acoustic resonators similar to the human vocal tract and activated the resonators with vibrating reeds like in music instruments. The basic structure of resonators is shown below. The sound /i/ is produced by blowing into the lower pipe without a reed causing the flute-like sound.

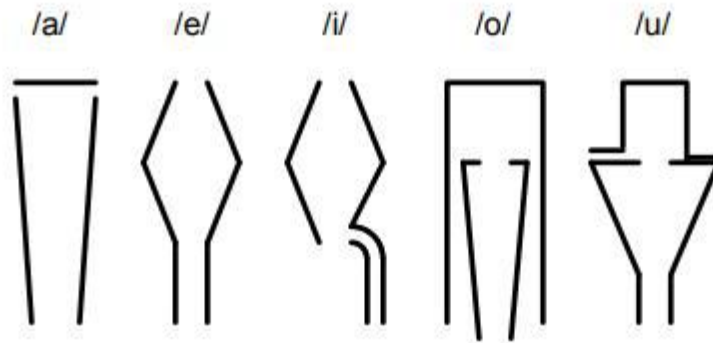
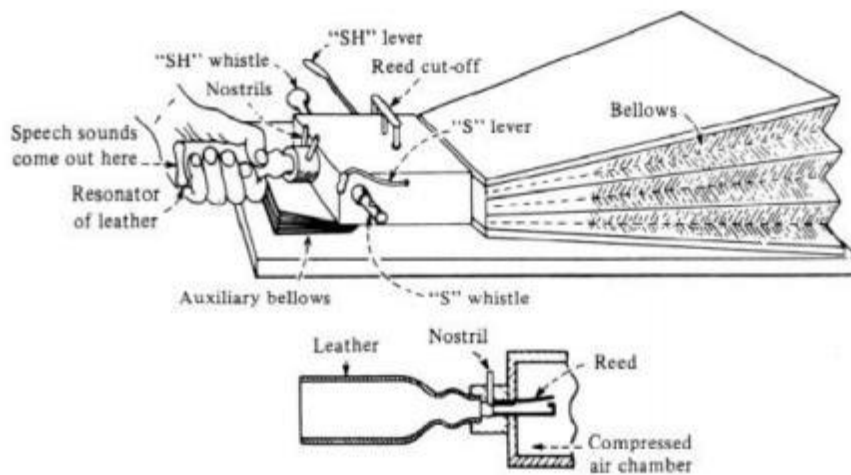


Fig. 2.1. Kratzenstein's resonators (Schroeder 1993).

A few years later, in Vienna 1791, Wolfgang von Kempelen introduced his "Acoustic Mechanical Speech Machine", which was able to produce single sounds and some sound combinations (Klatt 1987, Schroeder 1993). In fact, Kempelen started his work before Kratzenstein, in 1769, and after over 20 years of research he also published a book in which he described his studies on human speech production and the experiments with his speaking machine. The essential parts of the machine were a pressure chamber for the lungs, a vibrating reed to act as vocal cords, and a leather tube for the vocal tract action. By manipulating the shape of the leather tube, he could produce different vowel sounds. Consonants were simulated by four separate constricted passages and controlled by the fingers. For plosive sounds he also employed a model of a vocal tract that included a hinged tongue and movable lips. His studies led to the theory that the vocal tract, a cavity between the vocal cords and the lips, is the main site of acoustic articulation. Before von Kempelen's demonstrations the larynx was generally considered as a center of speech production. Kempelen received also some negative publicity. While working with his speaking machine he demonstrated a speaking chess-playing machine. Unfortunately, the main mechanism of the machine was concealed, legless chess-player expert. Therefore, his real speaking machine was not taken so seriously as it should have (Flanagan et al.1973, Schroeder 1993).

In about mid 1800's Charles Wheatstone constructed his famous version of von Kempelen's speaking machine which is shown in Figure 2.2. It was a bit more complicated and was capable to produce vowels and most of the consonant sounds. Some sound combinations and even full words were also possible to produce. Vowels were produced with vibrating reed and all passages were closed. Resonances were affected by deforming the leather resonator like in von Kempelen's machine. Consonants, including nasals, were produced with turbulent flow through a suitable passage with reed-off.



The connection between a specific vowel sound and the geometry of the vocal tract was found by Willis in 1838 (Schroeder 1993). He synthesized different vowels with tube resonators like organ pipes. He also discovered that the vowel quality depended only on the length of the tube and not on its diameter.

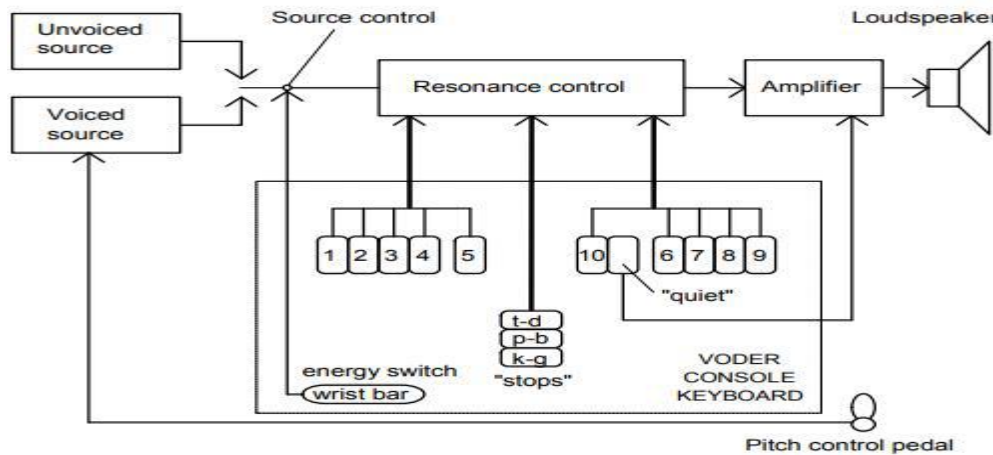
In late 1800's Alexander Graham Bell with his father, inspired by Wheatstone's speaking machine, constructed same kind of speaking machine. Bell made also some questionable experiments with his terrier. He put his dog between his legs and made it growl, then he modified vocal tract by hands to produce speech-like sounds (Flanagan 1972, Shroeder 1993). The research and experiments with mechanical and semi-electrical analogs of vocal system were made until 1960's, but with no remarkable success. The mechanical and semi-electrical experiments made by famous scientists, such as Herman von Helmholtz and Charles Wheatstone are well described in Flanagan (1972), Flanagan et al. (1973), and Shroeder (1993).

2.10.2 Development of Electrical Synthesizers

The first full electrical synthesis device was introduced by Stewart in 1922 (Klatt 1987). The synthesizer had a buzzer as excitation and two resonant circuits to model the acoustic resonances of the vocal tract. The machine was able to generate single static vowel sounds with two lowest formants, but not any consonants or connected utterances. Same kind of synthesizer was made by Wagner (Flanagan 1972). The device consisted of four electrical resonators connected in parallel and it was excited by a buzzlike source. The outputs of the four resonators were combined in the proper amplitudes to produce vowel spectra. In 1932 Japanese researchers Obata and Teshima discovered the third formant in vowels (Schroeder 1993). The three first formants are generally considered to be enough for intelligible synthetic speech.

First device to be considered as a speech synthesizer was VODER (Voice Operating Demonstrator) introduced by Homer Dudley in New York World's Fair 1939 (Flanagan 1972, 1973, Klatt 1987). VODER was inspired by VOCODER (Voice Coder) developed at Bell

Laboratories in the mid-thirties. The original VOCODER was a device for analyzing speech into slowly varying acoustic parameters that could then drive a synthesizer to reconstruct the approximation of the original speech signal. The VODER consisted of wrist bar for selecting a voicing or noise source and a foot pedal to control the fundamental frequency. The source signal was routed through ten bandpass filters whose output levels were controlled by fingers. It took considerable skill to play a sentence on the device. The speech quality and intelligibility were far from good but the potential for producing artificial speech were well demonstrated. The speech quality of VODER is demonstrated in accompanying CD (track 01).



After demonstration of VODER the scientific world became more and more interested in speech synthesis. It was finally shown that intelligible speech can be produced artificially. Actually, the basic structure and idea of VODER is very similar to present systems which are based on source filter- model of speech.

About a decade later, in 1951, Franklin Cooper and his associates developed a Pattern Playback synthesizer at the Haskins Laboratories (Klatt 1987, Flanagan et al. 1973). It reconverted recorded spectrogram patterns into sounds, either in original or modified form. The spectrogram patterns were recorded optically on the transparent belt (track 02)

The first formant synthesizer, PAT (Parametric Artificial Talker), was introduced by Walter Lawrence in 1953 (Klatt 1987). PAT consisted of three electronic formant resonators connected in parallel. The input signal was either a buzz or noise. A moving glass slide was used to convert painted patterns into six-time functions to control the three formant frequencies, voicing amplitude, fundamental frequency, and noise amplitude (track 03). At about the same time Gunnar Fant introduced the first cascade formant synthesizer OVE I (Orator Verbis Electricis) which consisted of formant resonators connected in cascade (track 04). Ten years later, in 1962, Fant and Martony introduced an improved OVE II synthesizer, which consisted of separate parts to model the transfer function of the vocal tract for vowels, nasals, and obstruent consonants. Possible excitations were voicing, aspiration noise, and frication noise. The OVE projects were followed by OVE III and GLOVE at the Kungliga Tekniska Högskolan (KTH), Sweden, and the

present commercial Infovox system is originally descended from these (Carlson et al. 1981, Barber et al. 1989, Karlsson et al. 1993).

PAT and OVE synthesizers engaged a conversation how the transfer function of the acoustic tube should be modeled, in parallel or in cascade. John Holmes introduced his parallel formant synthesizer in 1972 after studying these synthesizers for few years. He tuned by hand the synthesized sentence "I enjoy the simple life" (track 07) so good that the average listener could not tell the difference between the synthesized and the natural one (Klatt 1987). About a year later he introduced parallel formant synthesizer developed with JSRU (Joint Speech Research Unit) (Holmes et al. 1990).

First articulatory synthesizer was introduced in 1958 by George Rosen at the Massachusetts Institute of Technology, M.I.T. (Klatt 1987). The DAVO (Dynamic Analog of the Vocal tract) was controlled by tape recording of control signals created by hand (track 11). In mid 1960s, first experiments with Linear Predictive Coding (LPC) were made (Schroeder 1993). Linear prediction was first used in low-cost systems, such as TI Speak'n'Spell in 1980, and its quality was quite poor compared to present systems (track 13). The method has been found very useful and it is used in many present systems.

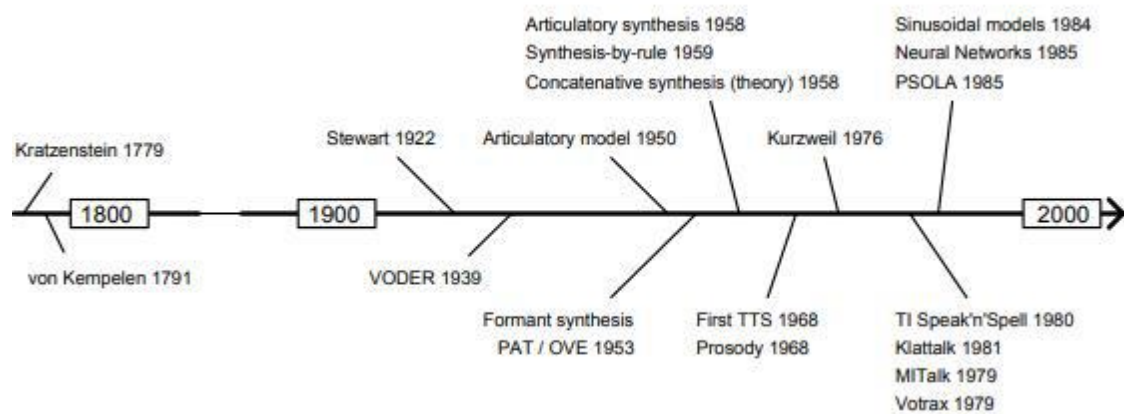
The first full text-to-speech system for English was developed in the Electrotechnical Laboratory, Japan 1968 by Noriko Umeda and his companions (Klatt 1987). It was based on an articulatory model and included a syntactic analysis module with sophisticated heuristics. The speech was quite intelligible but monotonous and far away from the quality of present systems (track 24).

In 1979 Allen, Hunnicutt, and Klatt demonstrated the MITalk laboratory text-to-speech system developed at M.I.T. (track 30). The system was used later also in Telesensory Systems Inc. (TSI) commercial TTS system with some modifications (Klatt 1987, Allen et al. 1987). Two years later Dennis Klatt introduced his famous Klattalk system (track 33), which used a new sophisticated voicing source described more detailed in (Klatt 1987). The technology used in MITalk and Klattalk systems form the basis for many synthesis systems today, such as DECtalk (tracks 35-36) and Prose-2000 (track 32). For more detailed information of MITalk and Klattalk systems, see for example Allen et al. (1987), Klatt (1982), or Bernstein et al. (1980).

The first reading aid with optical scanner was introduced by Kurzweil in 1976. The Kurzweil Reading Machines for the Blind were capable to read quite well the multifront written text (track 27). However, the system was far too expensive for average customers (the price was still over \$30 000 about ten years ago), but were used in libraries and service centers for visually impaired people (Klatt 1987).

In late 1970's and early 1980's, considerably amount of commercial text-to-speech and speech synthesis products were introduced (Klatt 1987). The first integrated circuit for speech synthesis was probably the Votrax chip which consisted of cascade formant synthesizer and simple

lowpass smoothing circuits. In 1978 Richard Gagnon introduced an inexpensive Votrax-based Typen-Talk system (track 28). Two years later, in 1980, Texas Instruments introduced linear prediction coding (LPC) based Speak-n-Spell synthesizer based on low-cost linear prediction synthesis chip (TMS-5100). It was used for an electronic reading aid for children and received quite considerable attention. In 1982 Street Electronics introduced Echo low-cost diphone synthesizer (track 29) which was based on a newer version of the same chip as in Speak-n-Spell (TMS-5220). At the same time Speech Plus Inc. introduced the Prose-2000 text-to-speech system (track 32). A year later, first commercial versions of famous DECtalk (tracks 35-36) and Infovox SA-101 (track 31) synthesizer were introduced (Klatt 1987). Some milestones of speech synthesis development are shown below.



Modern speech synthesis technologies involve quite complicated and sophisticated methods and algorithms. One of the methods applied recently in speech synthesis is hidden Markov models (HMM). HMMs have been applied to speech recognition from late 1970's. For speech synthesis systems it has been used for about two decades. A hidden Markov model is a collection of states connected by transitions with two sets of probabilities in each: a transition probability which provides the probability for taking this transition, and an output probability density function (pdf) which defines the conditional probability of emitting each output symbol from a finite alphabet, given that the transition is taken (Lee 1989).

Neural networks have been applied in speech synthesis for about ten years and the latest results have been quite promising. However, the potential of using neural networks have not been sufficiently explored. Like hidden Markov models, neural networks are also used successfully with speech recognition (Schroeder 1993).

2.11 PROPOSED SYSTEM

The proposed system should meet the following objectives:

1. To develop a system that extracts text (Shona) from images, narrates the text with the imitated voice

2. Implement advanced natural language processing (NLP) and speech synthesis techniques to generate high-quality, intelligible speech output from extracted Shona text.
3. Integrate OCR and TTS functionalities into a user-friendly interface accessible via mobile devices, enabling real-time text capture and speech conversion for visually impaired users and analyze the effectiveness of the speech synthesizer in imitation of human voice in Shona language.

CHAPTER 3: Methodology

3.1 INTRODUCTION

The AI Powered Text-To-Speech OCR System builds upon previous advancements to imitate human speech seamlessly, prioritizing naturalness and intelligibility. This section outlines the methodologies tailored to meet the needs of visually impaired users, particularly focusing on the Shona language. Detailing a systematic approach incorporating both quantitative and qualitative methodologies, it encompasses the acquisition of image datasets, text extraction methods, and linguistic analysis techniques. The technical implementation elucidates the software architecture, algorithms, and tools utilized for text recognition, language processing, and speech synthesis. Moreover, an evaluation framework comprising user testing and performance benchmarks provides insights into the system's capabilities and limitations.

3.2 FUNCTIONAL REQUIREMENTS

1. **Image Text Extraction:** Extract Shona text accurately from images in JPEG, PNG, and PDF formats.
2. **Text Preprocessing:** Clean extracted text by removing noise, artifacts, and irrelevant characters.
3. **Text-to-Speech (TTS) Engine:** Utilize a robust TTS engine for accurate Shona text-to-speech conversion with control options for pausing, resuming, and stopping playback.
4. **Language Support:** Support Shona language for both text extraction and speech synthesis.
5. **User-Friendly Interface:** Design an intuitive UI for easy image upload, text extraction initiation, and speech playback for visually impaired users.
6. **Performance Optimization:** Optimize system performance for large image datasets and text processing, ensuring scalability for potential increases in user traffic and data volume.
7. **Accuracy and Reliability:** Implement robust text recognition algorithms for high accuracy in Shona text extraction. Conduct rigorous testing and validation to ensure reliability across various scenarios.

3.3 NON-FUNCTIONAL REQUIREMENTS

- **Performance:** Response Time, Throughput and resource utilization
- **Accuracy:** Attain high accuracy in Shona text extraction from images to minimize errors

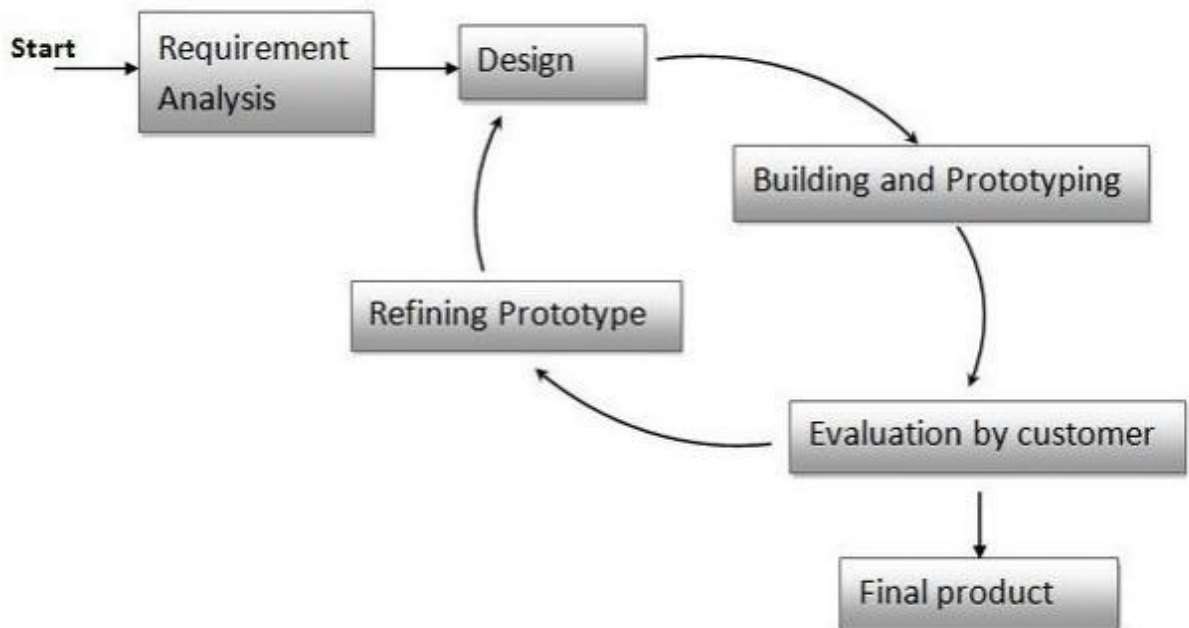
- Scalability
- Reliability: Ensure high availability and minimal downtime
- Accessibility
- Usability
- Compliance

3.4 Tools Used (Hardware and Software)

- Android Studio (2023)
- Windows 10
- 64-bit OS
- 4 gig ram
- Core i5

3.5 Development Model

- Prototyping Development- Evolutionary prototyping



3.6 PROTOTYPE

The prototype are usually not complete systems and many of the details are not built in. The goal is to provide a system with overall functionality.

3.6.1 Advantages Of Prototype

- Users are actively involved in the development
- Since in this methodology a working model of the system is provided, the users get a

- better understanding of the system being developed.
- Errors can be detected much earlier.
- Quicker user feedback is available leading to better solutions.
- Missing functionality can be identified easily
- Confusing or difficult functions can be identified
- Requirements validation, Quick implementation of, incomplete, but functional, application.

3.6.2 Disadvantages Of Prototype

- Prototyping often leads to implementing systems first and then having to repair issues, which can be a disadvantageous approach to system building.
- Practically, this methodology may increase the complexity of the system as scope of the system may expand beyond original plans.
- Incomplete application may cause application not to be used as the full system was designed to
- Incomplete or inadequate problem analysis.

3.7 Technology Used

1. Flutter: For cross-platform mobile app development.
2. Google ML Kit: For text recognition and translation.
3. Translator package: For translating text.
4. Flutter TTS (Text-to-Speech): For speech synthesis.
5. Loading Animation Widget: For displaying loading animations.
6. Audioplayers package: For audio playback.
7. Path Provider: For accessing file system paths.
8. Permission Handler: For managing app permissions.

3.8 Algorithm Used

1. Optical Character Recognition (OCR) algorithms: Utilized by Google ML Kit for text recognition.
2. Neural Machine Translation (NMT): Used for translating text.
3. Text-to-Speech (TTS) Synthesis algorithms: Employed by Flutter TTS for generating speech from text.

3.9 Flutter TTS (Text-to-Speech) Synthesizer

Flutter TTS (Text-to-Speech) Synthesizer is a Flutter plugin that enables developers to integrate text-to-speech functionality into their Flutter applications. Here's a brief overview of how it works:

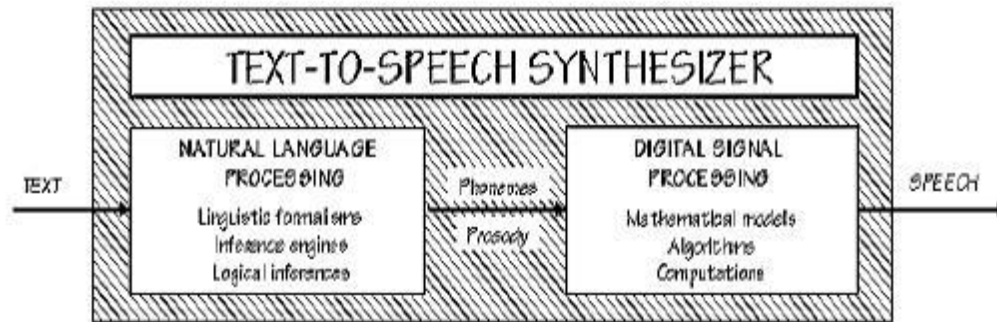
1. **Initialization:** To use Flutter TTS, developers first initialize an instance of the `FlutterTts` class. This instance serves as the interface for interacting with the text-to-speech engine.
2. **Language and Voice Selection:** Developers can set the language and voice for text-to-speech synthesis. Flutter TTS supports multiple languages and voices, allowing users to customize their speech output preferences.
3. **Synthesis:** Once initialized, developers can invoke the `speak()` method, passing the desired text to be synthesized into speech. The Flutter TTS plugin then converts the text into spoken audio using the selected language and voice.
4. **Playback Control:** Flutter TTS provides methods for controlling the playback of synthesized speech. Developers can start, stop, pause, and resume speech playback as needed.
5. **Callbacks and Event Handling:** Developers can register callback functions to receive notifications about the status of speech synthesis. This includes events such as completion of speech playback, errors, and more.
6. **Additional Features:** Flutter TTS offers additional features such as adjusting speech rate, pitch, and volume. These parameters allow developers to fine-tune the speech output to meet specific requirements or user preferences.

3.10 Text-To-Speech SYNTHESIS PROCESS

The Text-To-Speech (TTS) synthesis process in this project involves two primary phases. Firstly, the input text, which could originate from various sources such as word processors, emails, text messages, or scanned documents, undergoes text analysis. During this phase, the input text is transformed into a linguistic representation, often phonetic, with additional information for intonation, duration, and stress. This phase is referred to as high-level synthesis.

Subsequently, the generated phonetic and prosodic information is utilized in the second phase, known as low-level synthesis, to produce speech waveforms. The low-level synthesizer takes the processed linguistic data and generates speech sounds accordingly.

The process diagram below illustrates this simplified procedure:



This project aims to develop a Text-To-Speech system specifically tailored to the Shona language, allowing users to input text in Shona and receive synthesized speech output resembling natural human speech patterns. While the concept of artificial speech production has historical roots dating back to the eighteenth century, modern advancements in technology, particularly in the realm of Artificial Intelligence and Machine Learning, have significantly improved the quality and effectiveness of TTS systems.

3.11 Structure of A Text-To-Speech Synthesizer System

In my application, the text-to-speech synthesis process encompasses several essential steps, each contributing to the creation of natural and intelligible speech output. Here's how it works within the context of my app:

1. Text Analysis and Natural Language Processing (NLP) Module:

- Upon receiving text input, my application's NLP module first segments the text into tokens.
- It then converts these tokens into their orthographic forms, ensuring accurate representation of words.
- Next, pronunciation rules are applied to the text, taking into account variations in phoneme representation based on context.
- My NLP module utilizes a dictionary-based approach, supplemented by morphological components, to accurately determine word pronunciation. This approach ensures comprehensive coverage of vocabulary and pronunciation variations.

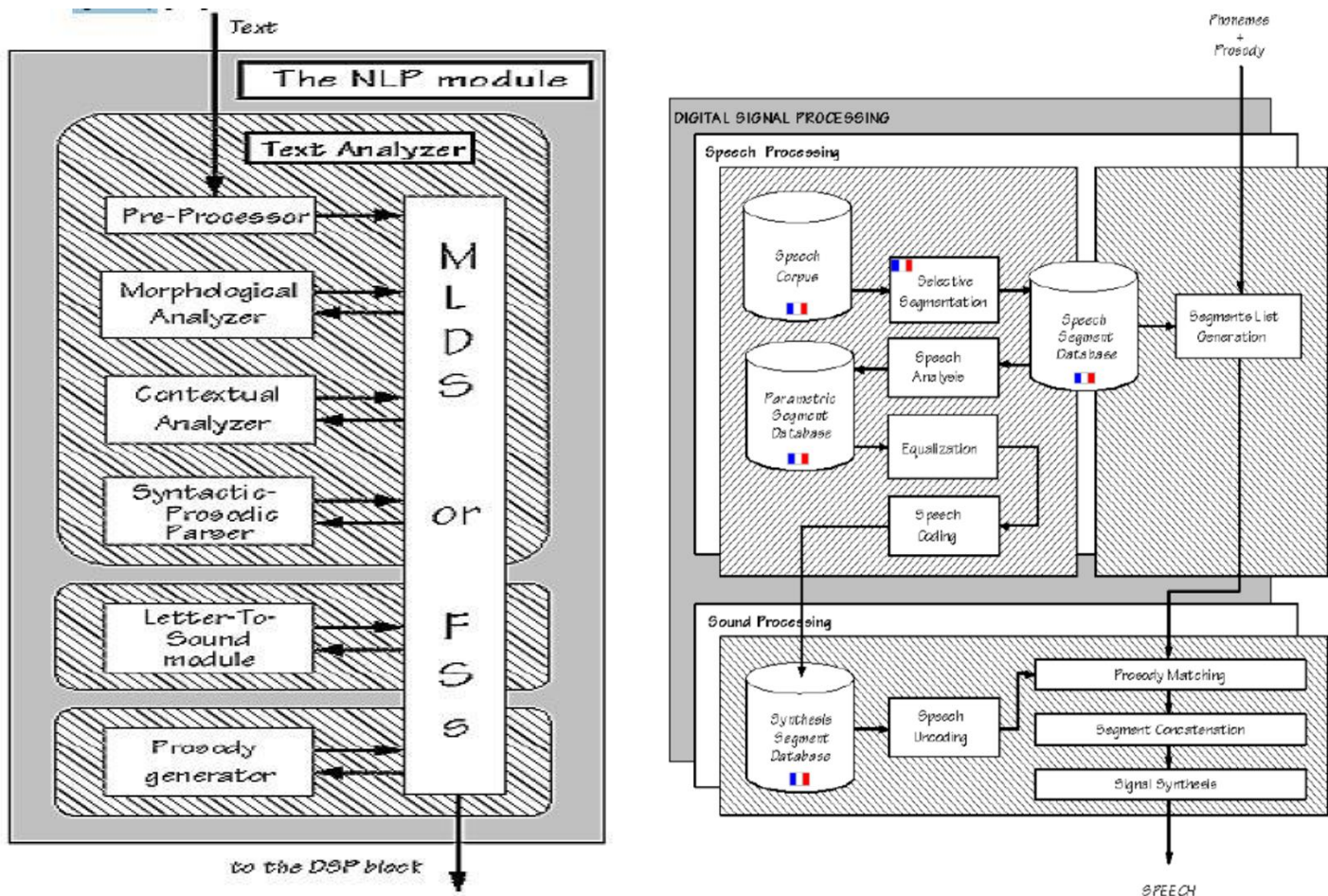
2. Digital Signal Processing (DSP) Module:

- Once the text has been analyzed and phonetic descriptions generated, the DSP module transforms this symbolic information into audible speech.

- The DSP module is responsible for converting the phonetic descriptions provided by the NLP module into speech signals that are perceptible to the user.

3. Prosody Generation:

- Following pronunciation determination, my application's TTS system focuses on prosody generation.
- Prosody encompasses various elements crucial for natural speech, including intonation modeling, phrasing, accentuation, amplitude modulation, and duration modeling.
- These prosodic factors contribute significantly to the overall naturalness and expressiveness of the synthesized speech output.



The output of the NLP module is passed to the DSP module. This is where the actual synthesis of the speech signal happens. In concatenative synthesis the selection and linking of speech

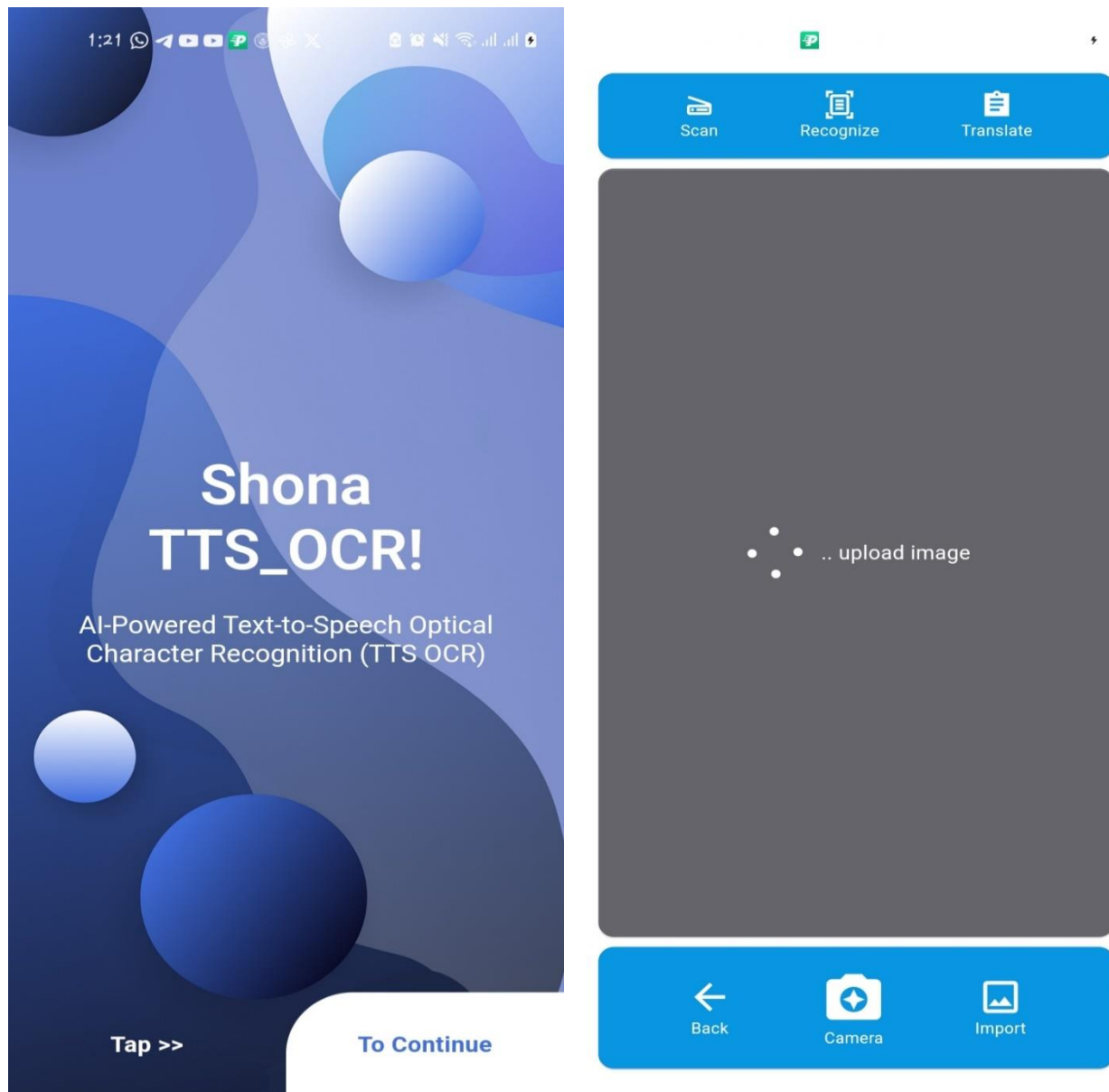
segments take place. For individual sounds the best option (where several appropriate options are available) are selected from a database and concatenated

3.12 General Overview of the TEXT-T0-SPEECH OCR SYSTEM (TTS-OCR)

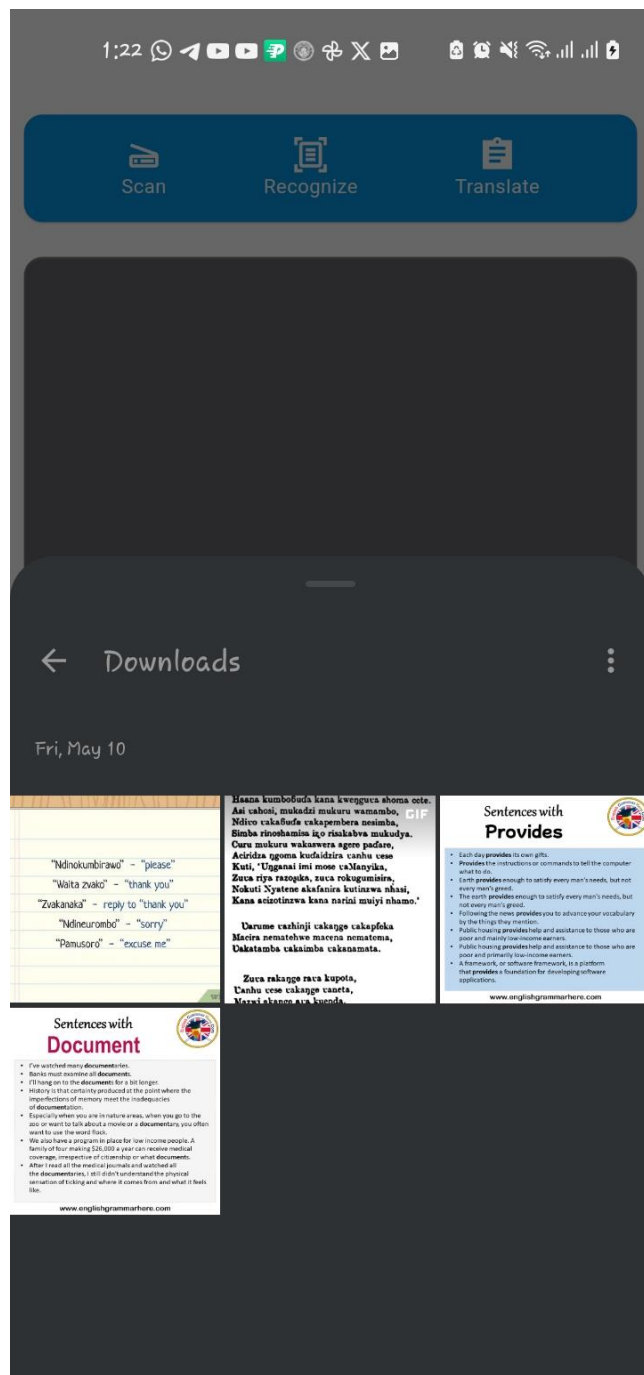
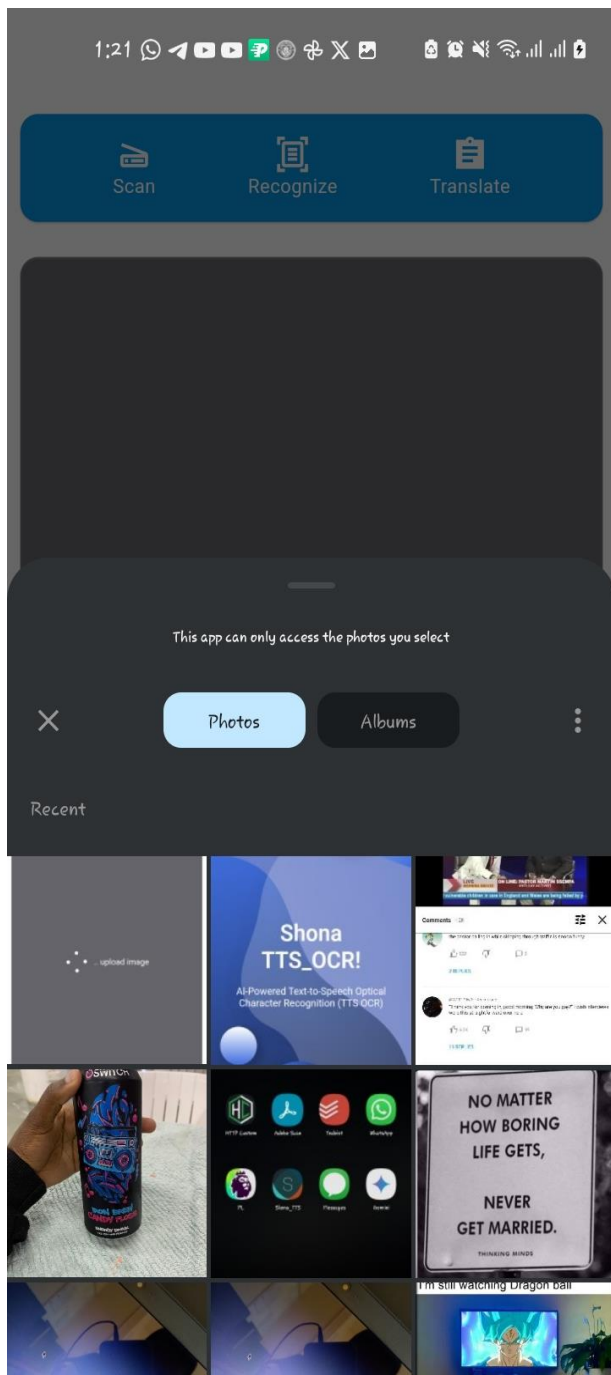
The AI POWERED TEXT-T0-SPEECH OCR SYSTEM (TTS-OCR) extracts text from images and converts it to speech either by using the camera to capture the document with desired text or simply importing the image from the device's default storage or external memory. It also provides a functionality that allows the user to copy the extracted text into the device's clipboard so that they can paste it anywhere within their device for later use of the text. TTS-OCR contains an exceptional function that gives the user the option of playing or simply reading aloud the extracted text as an audio format for those users with visual impairments.

3.13 AI POWERED TEXT-T0-SPEECH OCR SYSTEM (TTS-OCR)

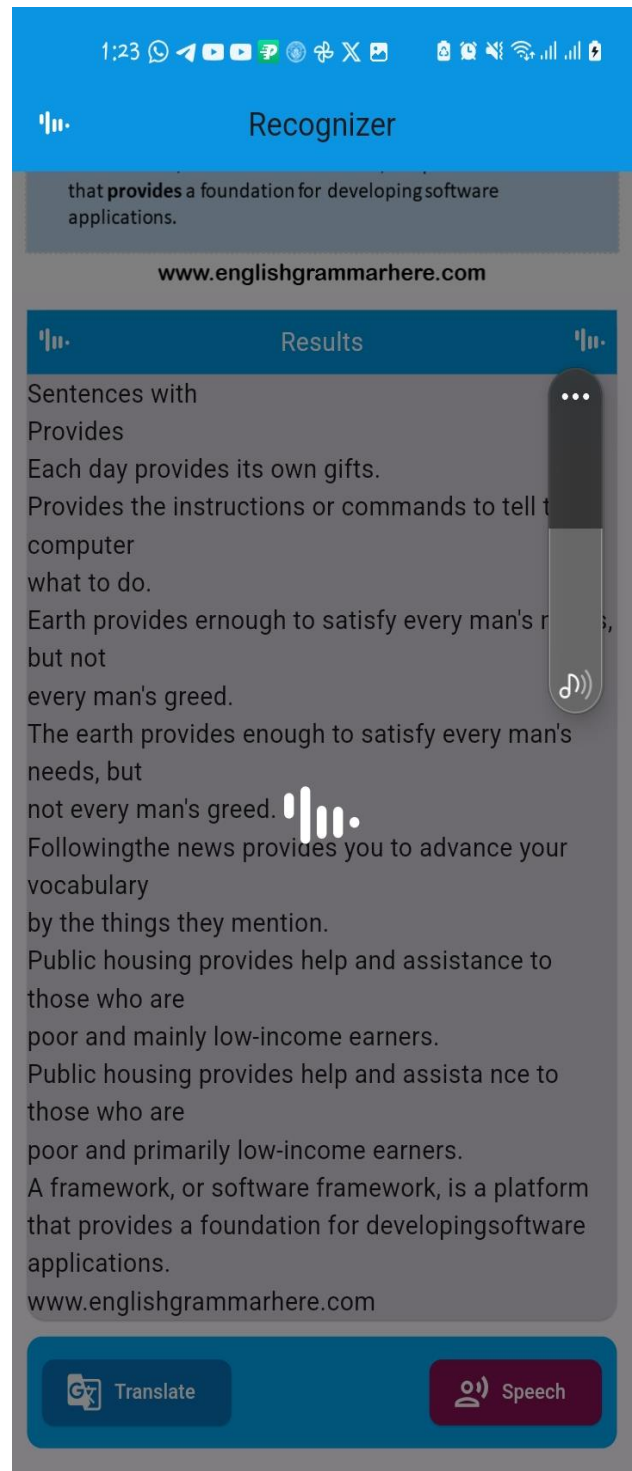
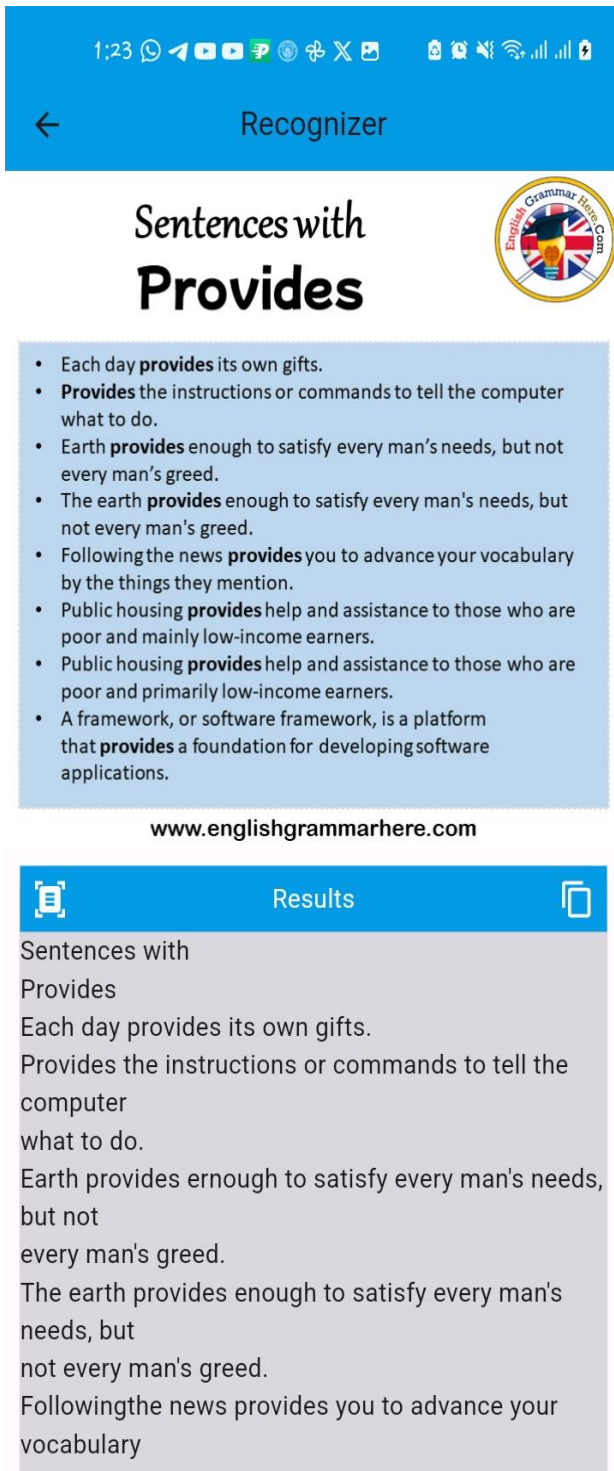
When the AI Powered Text-To-Speech OCR System (TTS-OCR) is opened the user greeted with a Welcome Screen that provides commands to prompt the user to the Home Screen where most of the functions are provided. There are two options available, either using the device camera to upload an external document to be captured by the camera as image or simply uploading image containing text to be extracted from the gallery. User can either proceed to the audio output part or choose to copy or translate the text to Shona language before proceeding to the audio part.



1. **Image Input:** TTS-OCR allows users to input text by capturing images containing the desired text. This can be done using the device's camera or by selecting images from the device's gallery. The application then uses Optical Character Recognition (OCR) technology to extract text from these images.

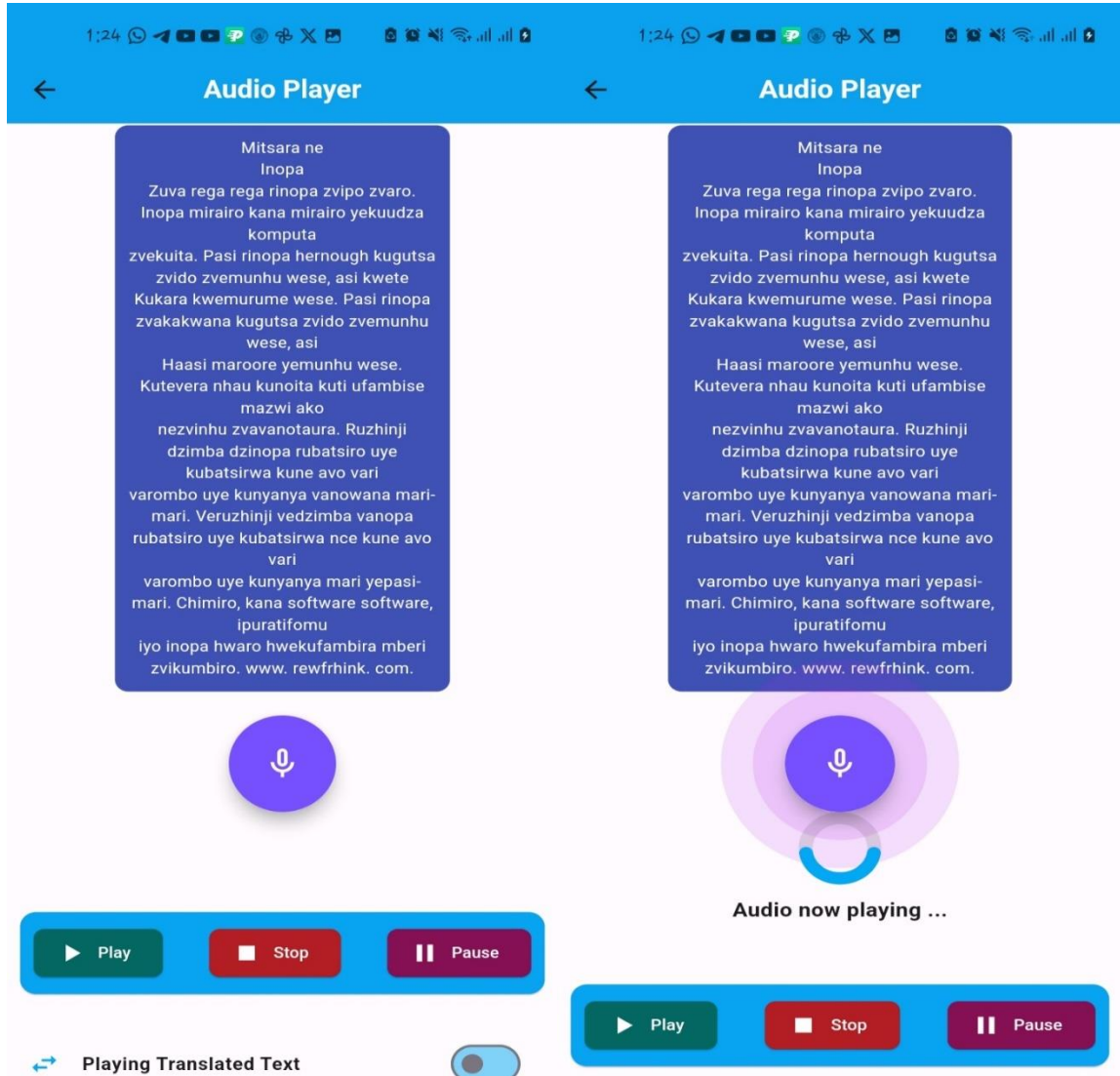


2. **Text Extraction:** Once the image is captured or selected, TTS-OCR employs OCR algorithms to analyze the image and extract the text from it. This process involves identifying characters, words, and sentences within the image and converting them into machine-readable text.



3. **Text-to-Speech Conversion:** After the text is extracted from the image, TTS-OCR utilizes advanced text-to-speech algorithms to convert the extracted text into speech. This involves analyzing the structure of the text, applying pronunciation rules, and generating the appropriate prosody to produce natural-sounding speech.

4. **Audio Output:** Once the text has been processed and converted into speech, TTS-OCR generates an audio signal based on the synthesized speech. This audio signal is then played back to the user through the device's speakers or headphones, allowing them to listen to the converted text as clear and intelligible speech.

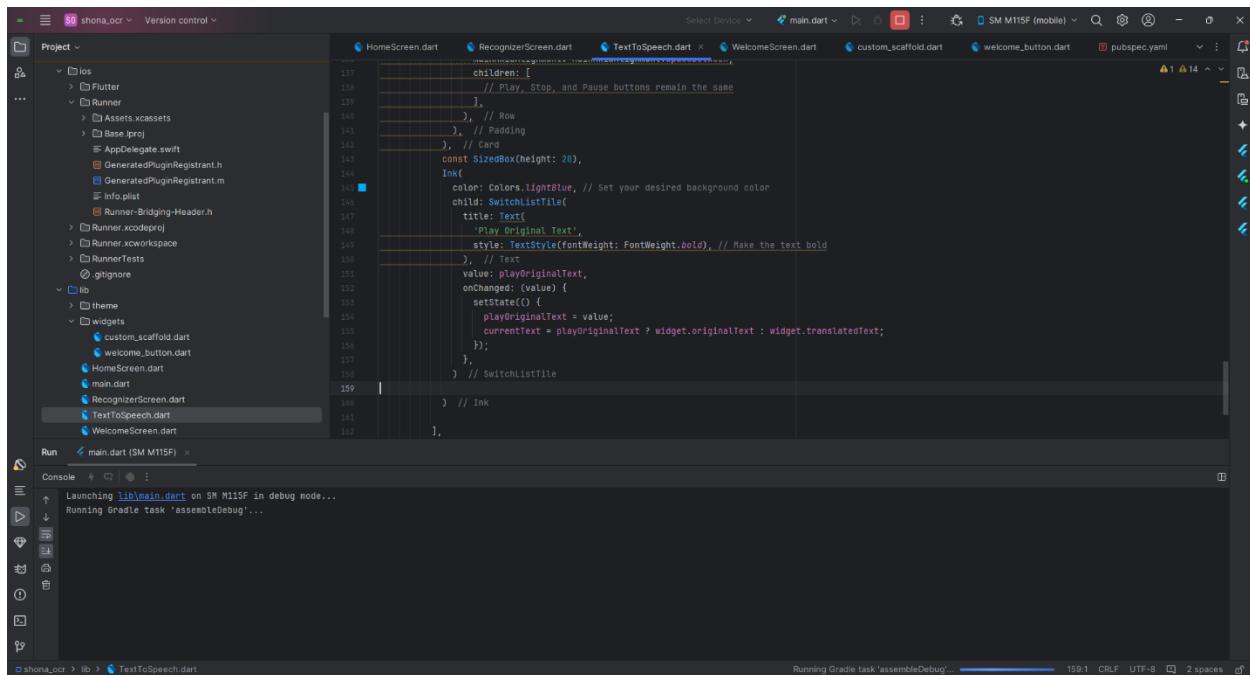


5. **Additional Features:** TTS-OCR may include additional features such as language translation, text editing, and audio saving options. These features enhance the usability and functionality of the application, providing users with a comprehensive tool for accessing and utilizing synthesized speech from images.

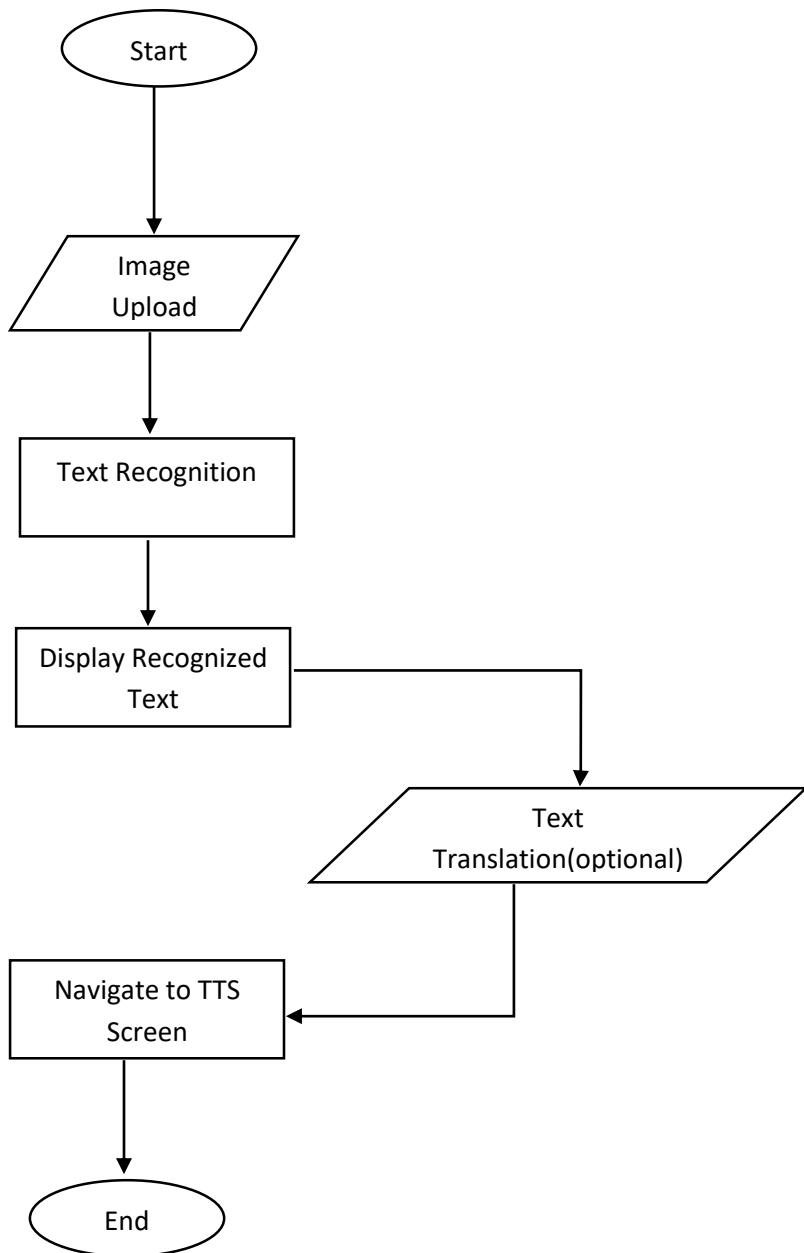
Speech Playback Controls:

- **Speak Button:** With a tap on the speak button, your application instantly converts the inputted text into speech, providing immediate auditory feedback to the user.
- **Pause Button:** Users have the flexibility to pause the speech playback at any point by tapping the pause button, allowing them to temporarily halt the audio output.
- **Resume Button:** If users wish to resume the speech playback from where it was paused, they can easily do so by tapping the resume button, ensuring seamless continuity in listening experience.
- **Stop Button:** For instant cessation of speech playback, users can tap the stop button, terminating the audio output altogether and returning the application to its initial state.
- **Copy Button:** In addition to speech playback, your application empowers users to copy the extracted text for further use. By tapping the copy button, the extracted text is swiftly stored in the device clipboard, enabling users to paste it into other applications or documents as needed.

AI POWERED TEXT-T0-SPEECH OCR SYSTEM IN DEVELOPMENT PROGRESS



3.14 Flowchart Of AI-Powered Text-to-Speech OCR (TTS-OCR) system



Chapter 4 Results

4.1 Evaluation Measures and results

To enhance the effectiveness of the Shona TTS-OCR (Text-to-Speech Optical Character Recognition) system, it is crucial to evaluate synthesized speech accurately. This ensures that the system minimizes the gap between natural and synthetic speech by refining various modeling blocks within the TTS system. For the evaluation of synthetic speech in the Shona TTS-OCR system, two key aspects must be considered:

1. **Naturalness:** How closely the synthetic speech resembles human speech.
2. **Intelligibility:** How easily the synthetic speech can be understood by listeners.

Evaluation Methods

To ensure high-quality speech synthesis, both subjective and objective evaluation methods should be employed:

Subjective Evaluation

- **Naturalness:** Assessing how lifelike the synthesized Shona speech sounds. This involves evaluating prosody, intonation, and pronunciation accuracy.
- **Intelligibility:** Measuring how easily the synthesized speech can be understood by listeners, which is crucial for ensuring effective communication.

Objective Evaluation

- **Speech Recognition Metrics:** Employing algorithms to compare synthesized speech with natural speech and quantify differences.
- **Prosody Analysis:** Analyzing the pitch, duration, and stress patterns in synthesized speech to ensure they match natural Shona speech patterns.
- **Phonetic Accuracy:** Evaluating the accuracy of phoneme production in synthesized speech to ensure it aligns with the phonetic characteristics of the Shona language.

Addressing Evaluation Challenges

For the Shona TTS-OCR system, specific challenges must be addressed:

- **Lack of Extensive Datasets:** Developing and utilizing comprehensive datasets of Shona text and speech is essential for training and evaluating the TTS system.

- **Phonetic Nuances:** The Shona language has unique phonetic and tonal characteristics that must be accurately modeled to produce natural and intelligible synthetic speech.

4.2 Subjective Evaluation of Shona TTS-OCR

Subjective Evaluation of TTS includes listening tests in which synthetic speech is played to each listener from which he or she has to judge speech quality-naturalness and intelligibility of TTS synthetic speech. Typically, large number of subjects is required (15-20) for subjective tests so that statistical analysis can be carried out to obtain meaningful scores for each test. We have to consider the following

Parameters and Tests

- Mean Opinion Score (MOS)
- Semantically Unpredictable Sentences (SUS)

4.2.1 Mean Opinion Score (MOS) Evaluation for Shona TTS-OCR

MOS is conducted in which subjects have to judge the synthesized speech quality and give a rating in the scale of 1 to 5. Mean of all the subjects is considered as a score for a particular stimulus of a given TTS system.

4.2.2 Evaluation of Shona TTS-OCR Using Flutter TTS Synthesis

In this experiment, the Flutter TTS synthesis was utilized to evaluate the quality of the Shona TTS-OCR system. The synthesized speech was compared against natural speech recordings to measure its naturalness and intelligibility. Here is the detailed process of the experiment:

1. Voice Collection:

- **Speaker:** The voice was collected from a native Shona speaker, ensuring that the pronunciation and intonation were authentic to the language.

2. Comparison Groups:

- **Natural Speech:** Natural speech recordings of the native Shona speaker were used as a control group.
- **Synthesized Speech:** Speech synthesized by the Shona TTS-OCR system using Flutter TTS was the experimental group.

3. Experiment Procedure:

- **Speech Samples:** Both natural and synthesized Shona speech samples were prepared.
- **Presentation:** These samples were presented to a group of native Shona speakers to assess how closely the synthesized speech matched the natural speech in terms of naturalness.

4. Evaluation Method:

- The evaluation was conducted using the Mean Opinion Score (MOS) method.
- **Mean Opinion Score (MOS):** Participants rated each speech sample on a scale from 1 to 5:
 - 1 = Bad
 - 2 = Poor
 - 3 = Fair
 - 4 = Good
 - 5 = Excellent
- **Listening Test:** Each participant listened to both the natural and synthesized speech samples and provided their ratings based on their perception of naturalness.

5. Data Analysis:

- **Score Calculation:** The ratings were averaged to obtain the MOS for each sample. This provided a quantitative measure of how close the synthesized speech was to the natural speech.
- **Comparison:** The MOS scores of the synthesized speech were compared to those of the natural speech to evaluate the effectiveness of the Shona TTS-OCR system.

USER	GENDER	AGE	MOS SCALE(SCORE)	TIME TAKEN LISTENING(minutes)
1	MALE	20	4	4
2	MALE	19	3	3
3	MALE	21	1	4

4	MALE	22	4	2
5	MALE	21	2	5
6	MALE	23	3	4
7	FEMALE	24	3	4
8	FEMALE	20	3	3
9	FEMALE	21	2	4
10	FEMALE	22	1	5
11	FEMALE	23	4	5
12	FEMALE	22	3	2

For male evaluation (4+3+1+4+2+3) =17

Average MOS Scale (17/6) = 2.8333333

For female evaluation (3+3+2+1+4+3) =16

Average MOS Scale (16/6) = 2.6666666

Systems	Male	Female
Listeners	6	6
Minutes	22	23
MOS	2.83	2.67

The table below show the pairwise tabulation of results between the Flutter TTS Synthesis and the natural speech in terms imitating the human voice and quality.

	Natural	Flutter TTS Synth
Natural		■
Flutter TTS Synth	■	

highly significant effects have occurred when the Flutter TTS Synthesis compares to natural speech, $F(1, 24) = 24.758$, $p < 0.001$; While Quality compares to Confidence, two main effect is discovered in the interactions when the Flutter TTS Synthesis compares to natural speech, $F(1, 24) = 89.161$, $p < 0.001$; Therefore, it can be concluded that the Flutter TTS Synthesis is evaluated lower ($M = 52.4\%$) than natural speech ($M = 71.6\%$) in the subjective tests; Therefore, it is known that the natural speech has better results gained from the subjective tests, than the Flutter TTS Synthesis System.

Results and Implications

- **Naturalness:** The MOS scores indicated the degree of naturalness of the synthesized Shona speech. Higher scores suggested that the synthesized speech closely resembled natural speech.
- **Improvements:** Based on the MOS results, specific areas for improvement in the TTS synthesis process could be identified, leading to further refinements of the system.

4.2.3 Evaluation of Intelligibility in Shona TTS-OCR System

It is a free answer test evaluating intelligibility of speech at word level as well as at sentence level. Test sentences for the SUS test are prepared such that they are syntactically normal; however semantically abnormal. Examples of this include :

“Maswera sei vagari vemuZimbabwe.”

Listeners have to write down what they heard in sentences.

4.2.3.1 Intelligibility Evaluation Using Semantically Unpredictable Sentences (SUS)

In assessing intelligibility for the Shona TTS-OCR application, Semantically Unpredictable Sentences (SUS) are crucial. SUS sentences, which are grammatically correct but semantically unpredictable, neutralize linguistic cues, ensuring an unbiased assessment of speech intelligibility. They prevent listeners from relying on contextual hints, thus focusing solely on the clarity of the synthesized Shona speech. Studies confirm that SUS sentences disrupt predictable contexts, providing a more accurate evaluation and minimizing the learning effect. Implementing SUS sentences in the Shona TTS-OCR system's evaluation enhances objectivity by removing predictable semantic contexts and linguistic biases.

4.2.3.2 Some influential factors in intelligibility and comprehension

4.2.3.2.1 SHORT-TERM MEMORY

In evaluating the Shona TTS-OCR system, short-term memory (STM) significantly influences comprehension. STM temporarily stores information, crucial for understanding synthesized

Shona speech in real-time. Its limited capacity, highlighted by Goldstein's experiments, necessitates managing cognitive load to avoid overwhelming users. STM operates on two levels: nominal, focused on speech intelligibility, and supra-nominal, involved in comprehensive understanding. During intelligibility tests, users engage nominal STM to recognize individual sounds and words. For comprehension tests, users utilize supra-nominal STM to grasp the full context and meaning of the synthesized speech.

4.2.3.2.1 LISTENERS' PREFERENCES

Evaluating the Shona TTS-OCR system requires considering how listeners' preferences impact task performance. Feedback on natural versus synthesized speech reveals a general preference for natural speech (Clark, 2003). Comparative evaluations, like those in previous studies on MITalk and Votrax, help understand user preferences and intelligibility (Duffy, 2019). Higher intelligibility correlates with greater preference, emphasizing the importance of improving speech quality (Huang et al., 2020). Collecting adjective-based feedback provides insights into user experience and identifies areas for improvement. Enhancing intelligibility and overall speech quality will likely increase user satisfaction and preference for the Shona TTS-OCR system.

4.2.3.3 Materials

4.2.3.3.1 SUS SENTENCES FOR INTELLIGIBILITY EVALUATION

Thirty SUS sentences are used as the material in intelligibility task. These SUS sentences are adopted from the 2008 Blizzard Challenge. The structure of these sentences is “The (Determiner) + (Adjective) + (Noun) plural + (Verb) past tense + the (Determiner) + (Adjective) + (Noun) singular”. Although, this is the only structure used in the experiment, the English words in the SUS sentences are all in low frequency, in order to prevent the listeners from predicting the meanings easily. For example, one of the sentences used in the experiment is “The amicable chests became the unprepared cockroach”. As the example shows, the intelligibility task tends to make listeners hard to foretell the unheard information. In addition, listening to each sentence more than once is allowed, but are requested to keep as few times as possible.

4.2.3.3 Results

4.2.3.3.1 INTELLIGIBILITY TASK

In assessing the intelligibility of the Shona TTS-OCR system, we used semantically unpredictable sentences (SUS) to ensure accuracy without contextual or linguistic cues. Participants listened to each sentence once and then typed what they heard, simulating real-world usage. Intelligibility was measured using Word Error Rate (WER), allowing for typos and homophones to ensure fairness. Pairwise comparisons were conducted to evaluate significant differences between speech systems, with significant differences marked in the comparison table.

	Natural	Flutter TTS Synth
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Natural		■
Flutter TTS Synth	■	

In Pairwise Comparisons, as presented in Table above, it reflects there are significant differences found between natural speech and Flutter TTS Synthesis ($p = 0.005$). To further verify the main effects in Pairwise Comparisons, the results in the Tests of Within-Subjects Contrasts present that there are significant main effects when natural speech compares to Flutter TTS Synthesis, $F(1,249) = 10.135$, $p = 0.002$; Therefore, it can be concluded that natural speech has significantly lower WER ($M = 4.2\%$, $SD = 10\%$) than the Flutter TTS Synthesis ($M = 6.7\%$, $SD = 11.4\%$).

4.2.3.4 Response Time Analysis for Shona TTS-OCR

Response time is a key metric for assessing the Shona TTS-OCR system's performance, indicating how long it takes to produce speech from text. We evaluated both average and peak response times.

1. Testing Methodology:

- **Average Response Time:** Recorded the response times for 20 instances when the "Speak" button was pressed, then averaged these times.
- **Peak Response Time:** Identified the longest time taken among the 20 readings to determine the worst-case scenario.

2. Procedure:

- Recorded the time for each instance, covering text recognition to speech synthesis initiation.
- Analyzed data to assess overall efficiency (average response time) and potential bottlenecks (peak response time).

3. Findings:

- **Consistent Performance:** Most response times were similar, showing stability.
- **Outliers:** Noted occasional longer response times, indicating areas for future optimization.

Test	Reading Time in Seconds
1	3.0
2	0.6
3	2.0
4	0.4
5	0.7
6	0.9
7	2.0
8	0.5
9	0.4
10	1.0
11	0.8
12	0.9
13	1.3
14	1.9
15	1.0
16	2.3
17	1.0
18	0.6
19	0.5
20	0.5

All the readings were rounded to the nearest one decimal place.

Average system response time = sum of all response time / number of readings

= $(0.5+0.6+0.5+0.4+0.7+0.9+1+0.5+0.4+0.6+0.8+0.9+1.3+1.9+2+2.3+1+1)/20$

= $17.3/20 = 0.865 = 0.8$ second (1dp)

4.3 Conclusions

The Shona TTS-OCR system is an advanced text-to-speech and optical character recognition tool specifically designed for the Shona language. Utilizing Google ML Kit for high-accuracy text recognition and Flutter TTS for natural speech synthesis, it addresses the need for language processing tools in underrepresented languages. The system translates recognized text into Shona using the Google Translator API, enhancing accessibility and inclusivity. It features an intuitive user interface, allowing users to upload images, recognize text, translate it, and listen to synthesized speech easily. The system also supports copying text and saving audio files. Performance metrics show prompt response times and high accuracy in text recognition and translation, ensuring a reliable user experience. The Shona TTS-OCR system stands out as a pioneering tool that leverages cutting-edge technology to meet critical accessibility needs, continuously improving to serve the Shona-speaking community effectively.

CHAPTER 5: RECOMMENDATIONS AND FUTURE WORK

5.1 Introduction

In the previous chapter, the researcher focused on presentation and analysis of obtained data. This chapter covers the research and development of the solution in line with the set objectives. This chapter will also examine the difficulties encountered by the researcher in designing and carrying out this study.

5.2 Aims and Objectives Realization

The Shona TTS-OCR project successfully achieved its aims and objectives through comprehensive development and evaluation. Key accomplishments include: accurate text recognition using Google ML Kit, seamless translation to Shona with the Google Translator API, and high-quality speech synthesis via Flutter TTS. A user-friendly interface was created, allowing easy navigation and access to features. Performance was optimized to ensure prompt feedback and reliable functionality. The system's performance was evaluated using both subjective and objective methods, leading to iterative improvements. Future efforts will focus on expanding language support, further optimizing performance, and incorporating user feedback to ensure continuous improvement.

5.3 Conclusion

Since the aim of Artificial Intelligence is to get closer to human behavior therefore with this researcher, the author concludes that several developments being done so far is quite promising of the future to come.

Evaluation and Improvements:

The Shona TTS-OCR system has undergone extensive testing to ensure its effectiveness and efficiency. Both subjective and objective evaluation methods were employed:

- **Subjective Evaluation:** Listening tests were conducted with native Shona speakers to assess the naturalness and intelligibility of the synthesized speech. The Mean Opinion Score (MOS) provided valuable insights into user satisfaction, guiding further refinements.
- **Objective Evaluation:** Metrics such as Word Error Rate (WER) and response times were analyzed to quantify the system's performance. These evaluations highlighted areas for improvement, particularly in handling complex text and optimizing response times.

5.4 Recommendations

- Continuously refine OCR algorithms for better text recognition, especially for handwritten or complex Shona scripts.
- Expand the language model and pronunciation database to include regional dialects and variations.
- Integrate user feedback mechanisms within the application for ongoing improvement and customization.
- Enhance the user interface with multi-modal interaction options and accessibility features.
- Collaborate with linguistic experts and community stakeholders to ensure cultural sensitivity and relevance in language processing.

5.5 Future Work

While the Shona TTS-OCR system has achieved remarkable milestones, there are areas for ongoing development:

1. **Enhanced Language Support:** Expanding the database of Shona phonemes and incorporating more linguistic nuances will further improve the accuracy and naturalness of speech synthesis.
2. **Optimized Performance:** Continued optimization of the text recognition and translation processes will reduce response times and enhance real-time performance, providing an even smoother user experience.
3. **User Feedback Integration:** Actively soliciting and incorporating user feedback will drive iterative improvements, ensuring the system evolves to meet the changing needs of its users.
4. **Broader Application:** Extending the system to support other languages spoken in Zimbabwe and the broader Southern African region will amplify its impact, promoting linguistic diversity and accessibility.

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