UNIVERSITI TEKNOLOGI MARA

COMPARATIVE ANALYSIS OF SPEECH DETECTION MODELS WITH A FOCUS ON THE JAPANESE LANGUAGE

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CHAPTER ONE
INTRODUCTION

1.1 Research Background

The way people interact with computers has changed rapidly throughout history. Initially, computer instructions were provided through punched cards. Nowadays, giving instruction to computers is simply by using voices. This advancement is made possible by using speech-to-text technology that converting the spoken language into text format (Wei Xu & Gao, 2023). Speech-to-text technologies has already existed in industries such as customer service and medicine. But with the advancement of the Machine Learning (ML) and artificial intelligence (AI), it has made the speech-to-text technology to become more precise and faster (Latif et al., 2020). These advancements have enabled its application across many areas, including transcription services and the development of inclusive tools for individuals with disabilities (Koenecke et al., 2020).

Although the speech-to-text technology has advance rapidly, it still has challenge like accurately transcribing Japanese language. According to Kanno (1996) in "An Introduction to Japanese Linguistics", Japanese language has may words that sound the same but have different meaning and to know which word is being used is based on the current context of the sentence. This is because Japanese language is using syllable-based word formation rather than individual phonemes, it means that the words are created using syllables like "ka", "ki' or "ku" instead of using a single consonant or vowel. Japanese language also using combination of three script with each has its own set of rule makes it harder to convert from spoken language to text.

With the advancement of machine learning and artificial intelligence, it has significantly improved speech recognition algorithms, enabling them to adapt to language nuances (Xu et al., 2023). This study investigates prominent models that is Whisper from Open AI, wav2vec2 by Facebook, and ChirpV2 an Universal speech model from Google. These models have their pros and cons when transcribing spoken Japanese into text and typically use learning frameworks and undergo training

on extensive datasets to improve accuracy in recognizing speech patterns (Ando & Fujihara, 2021). It is important to compare Japanese speech recognition systems because most research currently focuses on English or European languages, with limited exploration of how well these systems work with Japanese, especially in casual conversations and real-world contexts.

Only a few studies are comparing the Japanese speech recognition systems which created a gap in this area. It is important to examine how well these models can handle language feature like dialects and how well they able to transcribe spoken language based on accuracy and the speed to convert speech to text. The findings will contribute to the development of Japanese speech recognition technology.

1.2 Problem Statement

Current speech-to-text model are trained on standardized language which might not capture the complexities of Japanese language dialect and informal expression (Imaizumi et al., 2022). This has led to the models cannot perform well when transcribing the conversational Japanese especially when informal words or dialects is being used. Despite the advancements of AI, which significantly increase the quality of text-to-speech model (Karita et al., 2021), there is still lack of comprehensive evaluation between these models performance with Japanese language.

The lack of effective speech-to-text solution that tailored for Japanese language has its implication in industries. Industries that relying on speech-to-text technology such as telecommunication, education, technology, may face a problem because ineffective speech recognition can resulting in problems such as misunderstandings and will diminished the user satisfaction (Sztahó & Fejes, 2023). Additionally, the speech detection technology will not be adopted in industries if it fails to accurately capture the full spectrum of the language, limiting usability and accessibility (Widyana et al., 2022). Because of that, a study focused on Japanese speech recognition quality is important not only to improve practical outcome but also supports the ongoing advancement in AI field.

1.3 Research Objectives

1. To identify the key requirements for constructing speech-to-text model within the context of Japanese language.

2. To analyze speech-to-text models to determine the most effective techniques for reducing Word Error Rate (WER) and transcription latency in Japanese language processing.

3. To evaluate the WER and the transcription latency of different speech-to-text model when transcribing Japanese formal and informal language.

1.4 Research Questions

1. What is the key requirements for constructing speech-to-text model within the context of Japanese language.

2. What is the most effective techniques for reducing Word Error Rate (WER) and transcription latency in Japanese language processing.

3. How to calculate the performance and effectiveness of different speech-to-text model in context of Japanese language?

1.5 Scope of Study

This study will be focusing on examining the effectiveness of Automatic Speech Recognition (ASR) model for Japanese language speech-to-text technology. The key model is Whisper from OpenAI, wav2vec2 from Facebook's fined-tuned XLSR large language model, and the third model is Chirp, the next generation of Google's speech-to-text models. This study also will analyze the specific linguistic challenges that is unique in the Japanese language.

Some of the challenges is Japanese language using Syllable-based word formation that created many words that have same sounds but different meaning, which is crucial for the LLM to distinguish which word is being used based on the context of the sentence. On top of that, Japanese language also using three distinct writing

system that can be used in one sentence. So, it is also important to see how accurate the LLM transcribe the correct character from the speech.

After that the evaluation of each model performance based on how well it transcribing both formal and informal Japanese language will be carried out. Formal language is the language that is usually being used in professional setting where informal language is used in the daily life conversation. Then, this study will evaluate the model's performance based on its performance transcribing the different Japanese dialect.

Aside from the model accuracy, in this study also will be comparing the speed of the model to complete the transcription task. Speed is also one of the important aspects when the model is being used in real-time application where any delay will cause impact on the user experience. By evaluating both the accuracy and processing speed of the model, this study aims to identify which model is high in performance with minimal latency.

1.6 Significance of Study

This study is aimed to address the gap of effective speech-to-text solution that focusing on Japanese language. Most of the developed models is focusing on English language or a generic transcribe model that is developed for multi-language. In this study, the industry implication that caused by the inefficiency in speech to text technology in industries such as telecommunication and technology will be highlighted.

This study also contributes to the research by identify the current gaps in speech to text LLM, mainly in complex structured language like Japanese. This is achieved by offering a comparative analysis on which model is the best performance that can guide future improvement and innovation. This study aims to increase the effectiveness of speech to text adoption thus enhance the real-world application that rely on efficient transcription.

1.7 Conclusion

In this chapter, the advancement in machine learning and artificial intelligence that made the computer can understand human better by improving the speech to text

model accuracy and speed has been discussed. However, there is still challenges to transcribe a language that has complex structure like Japanese that include syllable-based formation and the use of multiple writing systems. Because of this, a study to find which implementation and which model is the most performance for handling Japanese language. The finding from this study is very important to answer the question of which model is the best for speech-to-text solution in Japanese language. By identifying the specific linguistic challenges and comparing these models, this study will provide a valuable information that will be able to guide future advancements in speech-to-text technology in Japanese language and ultimately will be able to support its broader application across the industries that rely heavily on precise and efficient transcription.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

The technology for Automatic Speech Recognition (ASR) has advanced rapidly in these years. Starting from traditional models like GMM and HMM into more sophisticated deep learning approaches such as DNN, CNN, RNN, and Transformer-based architectures.

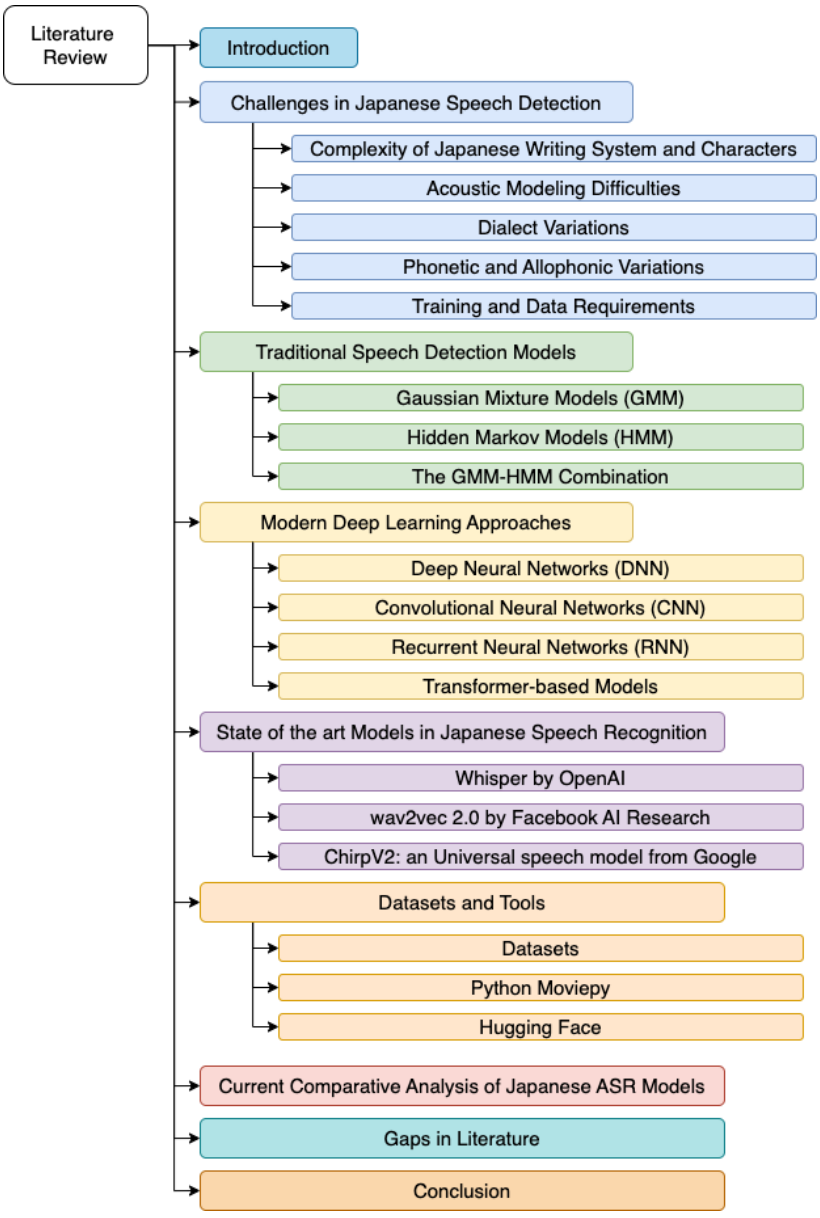

Figure 2.1 Literature Review Mind Map

However, to apply these technologies to the Japanese language may pose few challenges due to its complex writing systems, phonetic ambiguities, and dialectal variations. In this chapter, the challenges of Japanese speech detection and the traditional and modern ASR models will be reviewed. The state-of-the-art model like Whisper, wav2vec, and Chirp will also be discussed based on their applicability to Japanese. By identifying the key challenges and gaps in existing research, this chapter prepared for a focused analysis of Japanese-specific ASR systems.

2.2 Challenges in Japanese Speech Detection

2.2.1 Complexity of Japanese Writing System and Characters

The complexity of Japanese writing system and character can cause challenge in ASR system especially in end-to-end neural network architectures. Japanese writing system is a combination of multiple character sets, such as the Hiragana, Katakana, Kanji (ideographic characters), Roman letters and various symbols, leading to a considerably larger and more varied character (Rose, 2019). As mentioned by Ito et al. (2016, 2017), the number of possible Japanese character labels can exceed several thousand.

A single character of kanji may have a few ways to pronounce it because each character of kanji has Onyomi (Chinese derived) and Kunyomi (native Japanese) readings, and these readings can change depending on the word context (Curtin, 2020). Because of this ambiguity, the ASR system must be able to model and distinguish numerous acoustic differences in the speech data with same sound. The training model must be able to handle thousands of character and each of the character is potentially linked to multiple context dependent phonetic outcome which require a significant computational resources and large scale training data to ensure adequate coverage (Ito et al., 2016, 2017).

2.2.2 Dialect Variations

Another notable challenge in Japanese speech detection is dialectical variation that exist in the language. These dialects usually different from the standardized Tokyo based variety that is referred to as standard Japanese (Takahashi et al.,

2024). As mentioned by Imaizumi et al. (2020) that simply merging merging dialectal data with standard Japanese data into a single multi-condition training set often proves insufficient. The dialect specific pattern become saturated and leads to inefficient modelling and reduce the recognition accuracy. This issue can be addressed by integrating dialect labels as auxiliary features within the end-to-end ASR modeling framework. By explicitly encoding dialect information into the model, the recognition performance is improved by 19.2% relative error reduction (Imaizumi et al., 2020).

Another approach suggested by Imaizumi et al. (2022) is by employs a multi-task learning framework that able to optimize both dialect identification (DID) and multi-dialect ASR. This is achieveable by jointly training for dialect classification and ASR, the system exploits the strong interdependencies between acoustic-phonetic cues that is important for identification of dialectal features and linguistic structures that is crucial for accurate transcription. Three proposed architectures on how DID and ASR are integrated are as below:

1. DID2ASR: First performs dialect identification, then uses the predicted dialect label to inform ASR decoding.

2. ASR2DID: Reverses the order, first performing ASR and then using the recognized text to identify the dialect.

3. DID+ASR: Conducts dialect and ASR prediction jointly, using distributions over dialect classes rather than a single predicted label.

From these experiments demonstrate that multi-task learning with DID and ASR reduces word error rates and improves dialect classification accuracy (Takahashi et al., 2024).

2.3 Traditional Speech Detection Models

2.3.1 Gaussian Mixture Models (GMM)

GMM have been the earliest technology used for developing Japanese speech detection and recognition systems because of their capability in capturing the statistical distribution of speech features very well (Imaishi & Kawabata, 2022). Because of

the absence of word boundaries and the nuances of pitch accent in the Japanese language, it is really complicated to understand the context of the spoken words. However, GMM would be useful by employing probabilities to manage and characterize intricate patterns (Sun & Chol, 2020). For example, Povey et al. (2011) were able to use GMM to model phoneme-based acoustic features, and this approach led to a good performance of speech recognition systems.

Imaishi and Kawabata (2022) developed an approach within the EM algorithm that leads to the stabilization of the GMM parameters as well as increasing the discriminative power of the model in cases where there is not much evaluation data available. In other work, Povey et al. (2011) point out that it is possible to represent the distribution of speech features in GMM mode by employing a combination of several Gaussian components. This way the GMM ca n account for the phonetic or speaker variability which is known to be present during word is being pronounce.

Takami and Kawabata (2020) emphasized a different direction which starts with the creation of the Universal Background Model, which is a Gaussian Mixture Model calculated from the collection of a large number of speech samples from every dialect. To develop a model of the characteristics of a given UBM, the UBM is modified through Maximum A Posteriori (MAP) Adaptation. This method adjusts parameters of the UBM such as mean vectors, covariance matrices, and mixture weights depending on the individual's data (Dehak et al., 2009). Studies also have shown that the use of speaker factor space constructed in the GMM and Joint Factor Analysis (JFA) can greatly improves the accuracy and efficiency of GMM systems (Matrouf et al., 2011).

2.3.2 Hidden Markov Models (HMM)

HMM is working quite well with Japanese speech detection because of the incorporation of the acoustic and temporal characteristics of speech, including the difficulties found in the encoding of Japanese speech (Tokuda, 1999). Moreover, HMM is so useful in ASR because they are very efficient in the representation of time varying systems by a succession of discrete time states. A unique segment of the speech signal is represented in each state, and the segment is described using a specific set of acoustic features (Juang & Rabiner, 1991). ASR systems incorporated with

HMM are more superior in portraying Japanese speech characteristics' rhythm and tone including essential features like pitch accent and moraic timing which features will enhance the performance of the systems on the phonology aspects of the language (Tokuda, 2000).

ASR systems based on HMMs give quite satisfactory results especially on languages like Japanese because it is a possible to interpolate between a discrete set of states, where each state stands for a segment of the speech signal that has distinct acoustic features like pitch, duration, and phoneme quality (Juang & Rabiner, 1991). To further Increase Japanese ASR project, few other models is used along with HMM which is context-sensitive such as Tri-phone method. Tri-phone method is a phonetic expansion that employs phonetics of the neighbor sounds to the phoneme as context in order to increase the recognition accuracy by taking into account the co-articulation that takes place during fast speech production (Tokuda, 2000). Other models by Gales and Young (2008) were used together with HMM are Maximum Mutual Information and Minimum Phone Error which are useful for optimizing the parameters of the HMM and improve the recognition performance.

2.3.3 The GMM-HMM Combination

The GMM-HMM model uses GMM for the observation probabilities corresponding to each state of the HMM. Each state of an HMM is assumed to have a library of Gaussian mixtures with which the state's acoustic feature is pooled. Because transition probabilities of each state are determined by the HMM, temporal dependency of speech is well modelled. This combination allows the system to account for some of the variations in speech signals, such as those related to accent and the differences in the pronunciation of words in the Japanese language (Taheri & Taheri, 2006). While HMMs trained with large datasets under maximum likelihood criteria may have limited discriminative power, incorporating GMMs as observation models captures a broader range of acoustic variations. This method works really well for Japanese language, which are sensitive to the duration of phonemes in the context of the language.

Furthermore, the integration of GMM and HMM eliminates the need for applying state-of-the-art feature extraction techniques like Mel-Frequency Cepstral Co-

efficients (MFCC), hence increasing recognition performance (Sonali Nemade, 2019). This hybrid approach has been successful in speaker-dependent as well as in speaker-independent systems. When fuzzy clustering and the expectation-maximisation algorithm are used, lower error rates are usually obtained by GMM-HMM than the methods used in isolation. For example, in a paper on speech data collected in a noisy environment, it was demonstrated that GMM-HMM provided much improvement in recognition performance over the conventional HMM scheme (Sonali Nemade, 2019; Taheri & Taheri, 2006).

2.4 Modern Deep Learning Approaches

2.4.1 Deep Neural Networks (DNN)

The use of DNN in conjunction with HMM, also known as DNN-HMM has been shown to improve performance in Japanese speech recognition tasks. Seki et al. (2014) compared syllable-based and phoneme-based DNN-HMM and found that the syllable-based DNN-HMM was better, as its parameter space is less coupled with the context of the syllables. They reported that an 11% relative decrease in the WER for triphone DNN-HMMs over syllable-based DNN-HMMs when used on large databases such as ASJ+JNAS. The multilayered structure of DNNs makes it much suitable for developing models of contextual dependencies for speech signals (Hojo et al., 2018). GMM-HMM models are less effective compared to DNN when the task involves the estimation of posterior probabilities. In particular, pre-training with restricted Boltzmann machines has been quite useful for weight initialization, the vanishing gradient problem, and overall performance (Masato Mimura et al., 2013).

Mu et al. (2020) developed a double-deep neural network for the evaluation of Japanese pronunciation to address the problems of text-to-speech alignment and scoring. The DDNN integrated CNN and RNNs with attention and it is effective for detecting pronunciation mistakes. Lin et al. (2017) noted the importance of addressing the particular problem of the lack of annotated Japanese speech corpora by emphasizing the use of transfer learning with DNN. First, pre-training on large universal datasets increases the generalization ability. Then, fine-tuning on Japanese databases enhances the performance that is critical in low-resource applications. The authors

were also able to use CNN and recurrent architectures to attend to the granularity features of the Japanese language.

2.4.2 Convolutional Neural Networks (CNN)

There is difficulties in the visual speech recognition areas and specifically within lipreading because a limitation for the use of CNNs for phoneme recognition tasks was considered to be the number of training datasets (Noda et al., 2014). The research was conducted using elastic net regression on a seven-layer CNN structure and 58% of phoneme recognition accuracy was obtained for Japanese datasets. Building upon this work, Yalta et al. (2019) constructed a functional speech recognition framework inclusive of several types of words spoken intended for tight spots like houses. There are more focused methods for connecting microphones such as incorporating residual connections and batch denormalization.

Noda et al. (2014) investigated the use of CNNs for solving the problem of creating a Japanese speech acoustic model. CNN used to encode the frequency-time domain images and properly exploit the spatial and temporal aspects. The C-nets employed in this model aided in recognizing fine speech traits that improved performance in terms of recognition in contrast to the prevalent GMMs and HMMs methods. The combination of CNNs with attention mechanisms has yielded some results in the accurate detection of Japanese speech. This integration has been beneficial in increasing accuracy and interoperability during the detection of long utterances and multi-speaker datasets (Kohei Mukohara et al., 2015).

2.4.3 Recurrent Neural Networks (RNN)

In the work of Takeuchi et al. (2020), a novel design of the RNN is introduced, which enables the processing of input speech while removing noise caused by the room impulse response. This network mitigates the vanishing and exploding gradient problems often seen in RNNs while also keeping the parameter count low, making it very suitable for real-time applications. Yusuke Kida et al. (2016) investigated linear prediction filters based on LSTM. Their method trained an LSTM which did not require direct access to raw information and thus can extract features from distorted signals, as an LSTM estimated linear prediction coefficients.

Kubo (2014) broadened approaches incorporating RNNs into synthesizing speech for Japanese, particularly focusing on improving prosody and intonation. Their work underscored the necessity to consider the sequential modelling features of RNNs units, especially LSTMs, techniques for natural voice synthesis of Japanese language sounds. Takeuchi et al. (2020) took advantage of the RNN-based architectures for the acoustic modelling for Japanese ASR. They showed that even though GRUs have a simpler gating strategy than LSTMs, they could achieve a similar level of classification accuracy with lower compute requirements. Then, the studies on bidirectional LSTMs (BLSTMs). Imaizumi et al. (2022) revealed that they could utilise the past context and the future context of the signal for better performance of the speech recognition device. Many applications of automatic speech recognition in which the Japanese language is used have demonstrated that BLSTMs are particularly helpful for modelling complex phonological and prosodic structures of the Japanese language.

2.4.4 Transformer-based Models

Taniguchi et al. (2022) propose a series of Transformer-based ASR models aimed at improving Japanese speech recognition, particularly in the context of simultaneous interpretation. They investigate the possibility of utilizing auxiliary input like the source language text to resolve issues such as disfluencies, hesitations, and self-repairs commonly observed in the interpreter speech which helps to improve the transcription quality (Futami et al., 2020). The models combined audio and text data via multi-modal transformer encoders and decoders, which offers a broader scope of recognition by using previously provided source language text for interpreter training programs (Taniguchi et al., 2022).

A wide range of datasets for source text and simultaneous interpretation speech are however not readily available, so the authors use a adapted speech translation corpora from MuST-C and CoVoST 2 while also introducing TED based Japanese texts for evaluation purposes (Taniguchi et al., 2022). With an additional goal of enhancing performance, the authors fine-tune the source language text encoder by using large machine translation corpora which helps in lowering the word error rates during translation of English, Dutch, German and Japanese (Taniguchi et al., 2024). Results

consistently demonstrate that incorporating source language text into Transformer-based ASR models significantly improves recognition performance, with the greatest impact observed when auxiliary input is introduced at later stages of the audio encoding and decoding process (Futami et al., 2020).

2.5 State of the art Models in Japanese Speech Recognition

2.5.1 Whisper by OpenAI

Large scale weak supervision has emerged as one of the major approaches in speech recognition as noted by Radford et al. (2023) in their development of whisper model that has been trained on multilingual and multitask audio datasets that has a combined duration of 680,000 hours. This work is a continuation to the self-supervised methods such as Wav2Vec 2.0 (Baevski et al., 2020), which demonstrated learning without supervision from audio without any human-provided labels. However, dataset-specific fine-tuning is often necessary to obtain good performance, whereas with Whisper such reliance is reduced because of the efficacy of weak supervision.

By scaling weak supervision across diverse datasets, Whisper able to bypass the need for dataset-specific adaptation while able offer a robust zero-shot performance across languages and tasks. The authors also mentioned that by using this method, it will ensure the generalization and the robustness of the model while at the same time addressing main limitation in traditional models that is struggled to transcribe unfamiliar audio. This method also resulting in the models to have similar trends with other state of the art model in machine learning where a large, diverse datasets will improve model resilience which is align the with the advancements in computer vision (Kolesnikov et al., 2020) and NLP (Radford et al., 2019).The Whisper model's architecture, a simple encoder-decoder Transformer, reinforces the effectiveness of minimal preprocessing and sequence-to-sequence training, simplifying the transcription pipeline while achieving near-human-level accuracy.

Based on the work of Radford et al. (2023), there is further research that seeks to improve the performance of multilingual models on tasks that involve a japanese language. Bajo et al. (2024) detail their work on adapting OpenAI's Whisper model

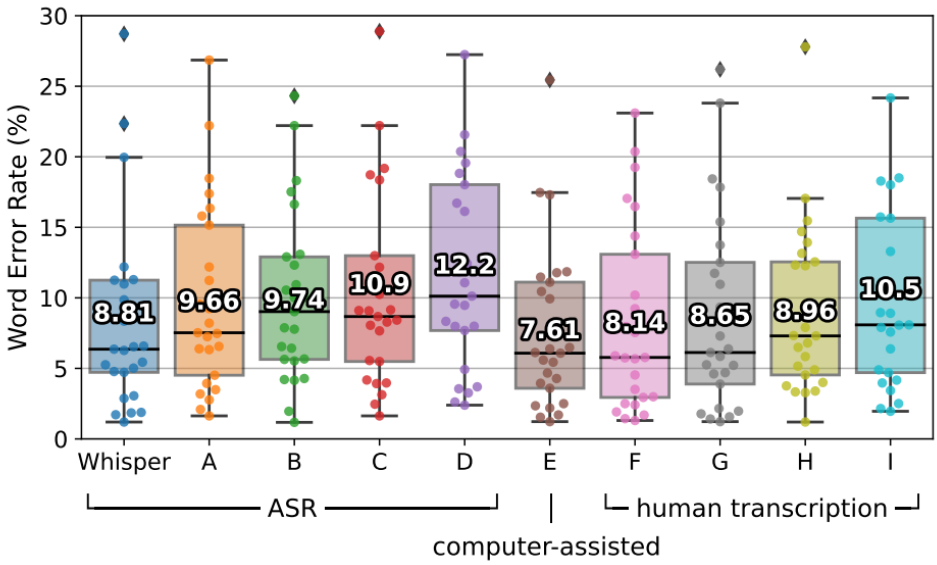

Figure 2.2 Whisper WER cited from Radford et al., 2023

to enhance its performance in ASR for the Japanese language. The research draws attention to the dilemma faced in balancing the multilingual being and the accuracy of an English-only product, ReazonSpeech, that seeks to maximize on the Japanese language ASR, which is monolingual in nature. By using a Japanese dataset while utilizing Low-Rank Adaptation (LoRA) and fine-tuning methods, they were able to lower Whisper-Tiny's Cumulative Expenditure Rate (CER) from 32.7% to 14.7%. This fine tuning method showed that smaller multilingual models give more promising result, after being tuned for the desired language outperform their larger baseline models, for example the case of the Whisper-Base model (Bajo et al., 2024).

Table 2.1
WER and CER performance of Whisper models. Reproduced from Bajo et al., 2024.

Model	**WER (%)**	**CER (%)**
Whisper Tiny	47.48	32.74
Whisper Base	29.81	20.20
Whisper Small	16.14	9.89
Whisper Medium	10.84	6.86
Whisper Large	7.41	4.77
Whisper Tiny + LoRA	33.16	20.83
Whisper Base + LoRA	23.36	14.50
Whisper Small + LoRA	14.90	9.16

2.5.2 wav2vec 2.0 by Facebook AI Research

The research conducted by Baevski et al. (2020) proved that self-supervised learning greatly reduces the dependency on large amounts of labeled data in speech recognition. They achieved this by using a technique called wav2vec 2.0. With this method, models are trained over a significant set of unlabeled speech data by masking the raw audio inputs and then treating a contrastive task. Thereafter, a model can be fine tuned using a limited set of labeled data which enables it to perform better when compared to semi-supervised techniques. Furthermore, according to Baevski et al. (2020), while their approach performed well with all the available labeled data by raising the WER to 1.8% for clean data and 3.3% for other data, it went even better with 10 mins of labeled and 53k hours of unlabeled data which had WER rates of 4.8% and 8.2%.

Table 2.2
WER on Librispeech dev/test sets using 10 minutes of labeled data and different unlabeled data setups.

Model	**Unlabeled Data**	**LM**	**dev (clean)**	**test (other)**
Discrete BERT	LS-960	4-gram	15.7	25.2
BASE	LS-960	4-gram+Transf.	8.9	15.6
		Transf.	6.6	12.9
LARGE	LS-960	Transf.	5.0	10.0
	LV-60k	Transf.	**4.6**	**8.2**
Highlighted Result	LV-60k (53k hours)	Transf.	**4.8**	**8.2**

In Japanese speech recognition, self-supervised learning (SSL) has emerged as one of the major tools for tackling the problems of dialectal diversity and low-resourced datasets. Miwa and Kai (2023) showcased what they refer to as successful adaptation of the wav2vec 2.0-based XLSR model to the Corpus of Japanese Dialects (COJADS), a collection of data capturing various dialects from different regions of Japan. They reported significant gains in ASR metrics for dialectal speech, achieving CER reductions of as much as 8.9% relatively to the models only trained on tagged data.

2.5.3 ChirpV2: an Universal speech model from Google

Zhang et al. (2023) demonstrated a novel technique that scales ASR to more than a hundred languages, this is achieved with the aid of large multilingual datasets with self-supervised learning, they refer to their model as the Universal speech model. The model was pretrained on 12 million hours of unlabelled audio data collection of 300 languages, in addition to 90 thousand hours of multilingual labelled audio data. One of the crucial innovations is BEST-RQ (BERT-based Speech pretraining with Random-projection Quantizer) because it improves the performance of speech representation without complicated quantization modules.

The model also outperformed specialized models including Whisper that have previously been trained with more data. In addition to this, chunk-wise attention is used to solve the performance drop-off problem that USM has with long audio, allowing USM to transcribe long audio. Other language resource enabling techniques such as noisy student training and adapter modules have enhanced USM performance with low resource and unseen languages considerably, as it did with low resource languages ensuring a robust ASR system (Zhang et al., 2023). USM proves the efficacy of self-supervised models in minimizing multilingualism and far supersedes existing standards for ASR systems.

Table 2.3
Word Error Rate (WER) Comparison of ASR Models

Dataset	**USM-CTC (%)**	**USM-LAS (%)**	**Whisper (%)**
YouTube (en-US)	13.7	14.4	17.7
YouTube (CORAAL)	18.7	19.0	27.8
SpeechStew (en-US)	26.7	29.8	-
FLEURS (62 languages)	12.1	11.2	13.2
Multilingual (YouTube)	15.5	12.5	23.9

2.6 Current Comparative Analysis of Japanese ASR Models

A comparative analysis that carried out by Karita et al. (2021) shows that Conformer-based models perform better than Conformer BLSTM architectures, as they obtained 4.1, 3.2, and 3.5 character error rates for CSJ in eval1, eval2, and eval3 tasks respectively. It is noted that both the BLSTM and Conformer models have character error rates below 7% and the character error rate is lower when using Con-

former Itself. Conformer encoders also offer increased accuracy and efficiency, with a throughput of 628.4 utterances processed per second and 430.0 for the BLSTM models. The scope of the work also emphasizes the importance of the analysis of the specific problem of training parameters optimization, noting the importance of the implementation of SpecAugment, exponential moving average (EMA) and variational noise (VN). The SpecAugment technique results in the largest shifts which affect the performance. The integration of the Conformer transducers with the described set of training approaches surpasses all existing solutions in Japanese ASR and open the path for further development (Karita et al., 2021).

Table 2.4
Character error rates on CSJ dev/eval1/eval2/eval3 sets cited from Karita et al., 2021.

Encoder	**Decoder**	**Param**	**Utt/sec**	**CER [%]**
BLSTM	CTC	258M	430.0	3.9 / 5.2 / 3.7 / 4.0
BLSTM	attention	309M	365.5	3.8 / 5.3 / 3.7 / 3.7
BLSTM	transducer	274M	297.6	3.8 / 5.1 / 3.7 / 4.0
Conformer	CTC	117M	**628.4**	3.1 / 4.1 / 3.2 / 3.5
Conformer	attention	124M	534.8	3.3 / 4.5 / 3.3 / 3.5
Conformer	transducer	120M	376.1	**3.1 / 4.1 / 3.2 / 3.5**

Another comparative analysis in the domain of the Japanese language is presented by Takahashi et al. (2024), focusing on the accuracy of speech recognition for different dialects. The study evaluates three models: Whisper, XLSR, and XLS-R, which are self-supervised learning frameworks. The Whisper model significantly underperformed for any Japanese outside of standard Japanese, recording a 4.1% CER only after it has gone through fine tuning. However, when the accuracy is low when the language identification marker is absent where some instances of being higher than 100%.This marks the weakness of Whisper in terms of its application for wide ranging applications in different dialects of Japanese. However, Whisperer and XLS-R both of which were trained on multilingual speech data show improvement in the recognition of Japanese dialects. These models apply multi-task learning paradigms such as DID and ASR to increase their efficiency. Multi tasking adds significantly to the dialect accuracy and a three-step efficient training of the models reduce the CER by 3-4% relative to conventional transfer learning. Some dialects, especially those from Kyushu and Chubu, have larger CER than those spoken in Kanto, where there is a greater linguistic affinity (Takahashi et al., 2024).

Current comparative analysis from these studies shows that several challenges need to be addressed. A study to compare the state of the art models in Japanese ASR is needed because from previously mentioned paper it is clear that the performance of the models varies depending on the dataset and the task. The Whisper model is the most accurate in the Japanese language, but it is not as effective in dialectal speech. The XLSR and XLS-R models are more effective in dialectal speech, but they are not as accurate as the Whisper model in standard Japanese. The Conformer model is the most accurate in standard Japanese, but it is not as effective in dialectal speech(Takahashi et al., 2024). The study will provide a comprehensive comparison of the state of the art models in Japanese ASR, which will help to identify the strengths and weaknesses of each model and to determine which model is the most effective for a given dataset and task.

Table 2.5
Comparison of ASR accuracy on two datasets, Standard Japanese (CSJ) and Japanese dialects (COJADS) cited from Takahashi et al., 2024.

Pre-Trained Model Name	**Adaptation Method**	**CER [%] CSJ**	**CER [%] COJADS**
Whisper-medium (zeroshot)	-	25.6*	116.0*
Whisper-medium	full finetuning	**4.1**	32.9
XLSR	full finetuning	6.5	34.1
XLSR	3-steps finetuning	-	30.0
XLS-R	full finetuning	6.1	32.6
XLS-R	3-steps finetuning	-	**29.2**

*After post-processing with kanji-to-kana conversion.

2.7 Datasets and Tools

2.7.1 Datasets

The dataset used in the Japanese ASR system is crucial for the performance of the model. The TED talks dataset is one of the most widely used datasets for Japanese ASR research (Afouras, 2018). This dataset contains speech data from TED talks in multiple languages, including Japanese. The TED talks dataset is useful for evaluating the performance of ASR systems on real-world speech data and for comparing the performance of different models.

Another dataset that is commonly used in Japanese ASR research is the Corpus of Spontaneous Japanese (CSJ). It contains 581 hours of spontaneous speech data,

which is divided into training, development, and evaluation sets (Ando & Fujihara, 2021). The CSJ dataset is annotated with phonetic, prosodic, and morphological information, making it a valuable resource for training and evaluating ASR systems.

For dataset that contain dialectical speech, the Corpus of Japanese Dialects (COJADS) is a valuable dataset that contains speech data from various Japanese dialects. It is especially useful for training ASR systems to recognize and transcribe different dialectical nuances, thereby enhancing system robustness in diverse linguistic contexts (Kibe et al., 2018).

2.7.2 Python Moviepy

MoviePy is a Python library for video editing that can be used to extract audio from video files. It provides a simple and intuitive interface for working with video and audio files, making it easy to extract audio clips from video files (Boishakhi et al., 2021). One of the key features to use MoviePy in this study is to extract audio from video files and convert them into a format that can be used for training ASR models.

2.7.3 Hugging Face

Hugging Face is a platform that provides a wide range of pre-trained models for natural language processing tasks, including speech recognition. It offers a variety of models that can be fine-tuned on custom datasets to improve performance on specific tasks (Boishakhi et al., 2021). In this study, Hugging Face will be used to access pre-trained models for Japanese ASR. These model will be downloaded from Hugging Face and analyze the performance of the models based on the dataset used in this study.

2.8 Gaps in Literature

Based on the literature review, shows that there is several gaps in the research on Japanese ASR. One of the area is the insufficient exploration of how state-of-the-art models can be adapted to the specific nuances of the Japanese language. Although there is few study that evaluate the performance of these model, but there is no notable research that focusing on evaluating the state of the art models in Japanese ASR. An-

other research gap from the literature review is the lack of focus on the performance of these models when dealing with dialectical variations of Japanese. Although research has been conducted on their effectiveness with standard Japanese, there is a clear need for further work on how these newly developed models perform when handling dialectical speech. Lastly, another gap identified is the underexplored area of these models application in real-time environments. Despite some investigations into their use in real-time scenarios, additional research is required to optimize these models for applications where quick response times are essential.

2.9 Conclusion

This chapter highlighted the challenges in Japanese ASR system that is its writing systems, phonetic variations, and dialectal diversity. The evolution of traditional ASR model to the cutting-edge technologies also has been highlighted in this chapter. Despite the advancements of the model and ASR framework, there is still a gap in adapting these models to Japanese-specific contexts, especially in handling informal speech and dialects. There is still work to be done to further refine the accuracy, speed, and dataset availability to advance Japanese ASR. This result can be used as a foundation for developing more effective and inclusive speech-to-text solutions tailored for Japanese language. For the dataset and tools, TED talks, CSJ, and CO-JADS are the most commonly used datasets for Japanese ASR research. To extract audio from video files, Python Moviepy is used and to access pre-trained models for Japanese ASR, the model will be obtain from Hugging Face.

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction

This chapter will be discussed about the methodology for evaluating Japanese ASR on three pre-trained speech recognition model that is OpenAI's Whisper, Meta's wav2vec 2.0, and Google's CHIRP Universal speech model (USM). This study will be focusing on comparing the Word Error Rate (WER) and transcription speed using formal (TED Talks) and informal (dialectal, COJADS) datasets. In this chapter, the data collection and data pre-processing steps such as audio conversion and resampling will be discussed. This chapter also will be discussing about the reason why the three model is selected and also the standardized testing environment. It concludes by discussing challenges, limitations, and ethical considerations relevant to the evaluation process.

3.2 Research Design

This study is conducted in four phase that is Preparation, Data Collection, Analysis, and Discussion. The details for each phase is described in the Table 3.1 below.

Table 3.1
Overview of the Research Methodology Plan

Phases	Activity	Methods	Deliverables
Phase 1 – Preparation	i. Define Area ii. Define Problem Statement iii. Define Research Objectives, Scope, Questions, and Significance	i. Review related articles and journals ii. Discussion with supervisor	Research Proposal & Chapter 1
Phase 2 – Data Collection	i. Study in detail the articles on the area of Speech Recognition ii. Identify challenges in Japanese ASR iii. Identify the most efficient techniques for improving WER and transcription latency	i. Literature Review ii. Data collection method: a) TED Talks YouTube dataset b) COJADS dataset iii. Data preprocessing	i. Target model selection ii. Processed audio files iii. Test environment setup
Phase 3 – Analysis	i. Evaluate the performance of the selected models ii. Calculate WER and transcription latency iii. Compare the models based on the evaluation metrics	i. Model testing and evaluation ii. Performance metrics calculation	i. Performance comparison results ii. Analysis of the models' strengths and limitations
Phase 4 – Discussion	i. Identify challenges and limitations ii. Summarize the research findings	i. Challenges and limitations identification ii. Research findings summary	i. Dissertation research report

3.3 Data Collection

3.3.1 Dataset Selection

To evaluate the performance of the models, this study will be using two sources of data. The first dataset is from Ted Talk Youtube dataset which will be responsible for formal speech with clear pronunciation completes with rich and diverse vocabulary. The second dataset is the Corpus of Japanese Dialects (COJADS) which will be responsible as the input for informal speech which categorized based on regional accent and expression. The COJADS dataset only can be obtain from National Institute for Japanese Language and Linguistics (NINJAL). Both of the dataset duration will be around 6 hours where duration for COJADS will be 1 hours for each

dialect sum up to 6 hours for dialectical speech. The duration of the dataset can be seen in Table 3.2.

Table 3.2
Dataset Audio Duration

Dataset	Dialect	Duration
TED Talks (YouTube)	Formal	6 hours
COJADS	Tōhoku	1 hours
	Kantō	1 hours
	Chūbu	1 hours
	Kansai	1 hours
	Shikoku	1 hours
	Okinawa	1 hours
Total		**12 hours**

3.3.2 Data Pre-processing

The pre-processing steps is the first step in doing the model comparison. This step will be focusing in preparing the datasets to be use as input into the selected speech recognition models. For the TED Talks YouTube dataset, the audio files will be extracted from video recordings and transcribed using Python Moviepy library into Waveform Audio File Format (WAV) format.

Listing 3.1: Python code to convert video to WAV format using moviepy

```
def convert_video_to_wav(video_path, output_wav_path):
try:
    video_clip = VideoFileClip(video_path)
    audio_path = output_wav_path\
        .replace(".wav", "_temp_audio.mp3")
    video_clip.audio.write_audiofile(audio_path)
    return audio_path

except Exception as e:
    return None
```

After that, each audio file was converted to the standardized 16 kHz format to ensure the data is compatible with the ASR models. Then the text will be manually transcribed and aligned with the corresponding audio to create accurate transcriptions for evaluation phase later.

For the COJADS dataset, the data is in MP4 format and the audio files will be extracted to wav using the same method as the TED Talks YouTube dataset. Then the audio files will be resampled to the 16 kHz format using Pydub library from Python.

Listing 3.2: Python code to resample audio to 16 kHz using pydub

```
def resample_audio(input_audio_path, output_audio_path,\
    target_sample_rate=16000):
try:
    audio = AudioSegment.from_file(input_audio_path)
    audio = audio.set_frame_rate(target_sample_rate)
    audio.export(output_audio_path, format="wav")

    print(f"Resampled audio saved to {output_audio_path}")
except Exception as e:
    print(f"Error during audio resampling: {e}")
```

The reason for resampling the audio into 16 kHz is that many modern ASR models are trained on and optimized for audio data sampled at this rate (Gergen et al., 2016). By standardizing the sample rate, the input data compatibility with the expected model parameters can be ensured, thus helping to avoid potential performance issues due to mismatched sample rates or quality. Additionally, a 16 kHz sampling rate provides a good balance between audio quality and computational efficiency, making the ASR systems both accurate and faster to process. Image 3.1 shows audio before and after resampling.

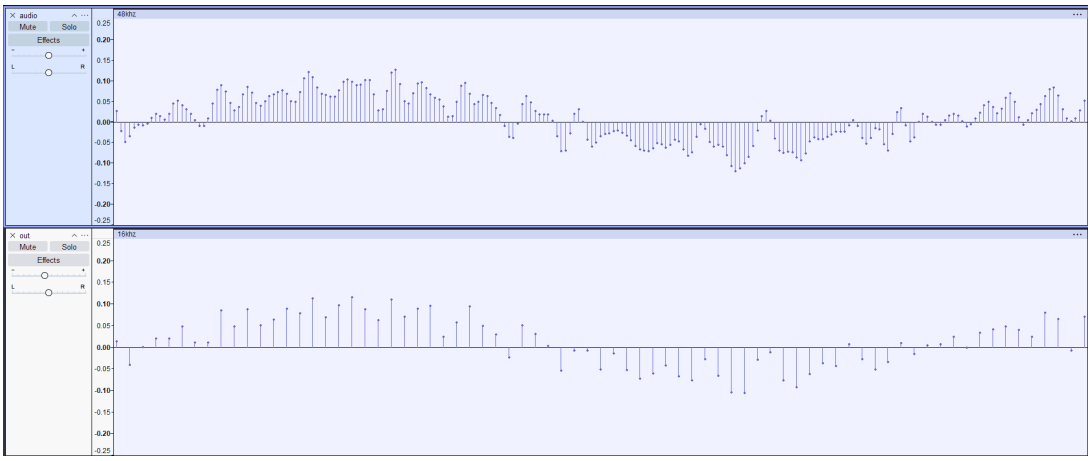

Figure 3.1 Audio resampling from 44.1 kHz(Top) to 16 kHz(Bottom)

3.4 Model Selection

3.4.1 Model Architecture Selection Criteria

Based on the findings from Literature review, the traditional GMM and HMM were not selected because of their limitations when dealing with the complex structure of Japanese language. GMMs are computationally inefficient and have trouble scaling for Japanese phonetics, dialects, and informal speech, even if they perform well when handling temporal variability and pitch accents. Similar to this, HMMs lack the flexibility and capabilities of contemporary deep learning models and are only useful for sequential data.

Large datasets and strong feature extraction enable DNN to greatly increase recognition accuracy. However, without intensive pretraining, they are unable to handle contextual dependencies and dialectical fluctuations. RNN, specifically Bidirectional LSTMs (BLSTM), are excellent at modelling sequential data and fixing pitch accent difficulties, but their scalability is limited by their computational inefficiency and potential for vanishing gradient concerns. In similar fashion, CNN are effective at recognizing time-frequency features and acoustic patterns, but they are deficient in contextual awareness for longer sequences and a variety of Japanese dialects. However, CCN is still used in wav2vec 2.0 model for feature extraction.

Transformer-based models have a very good performance in ASR due to their ability to process long sequences with attention mechanisms. In Japanese ASR tasks, conformer models especially perform more effectively than conventional and older neural network models. Because of this, transformer-based model has been chosen as the target models for this study. .

Table 3.3
Architecture Comparison of Traditional, Modern, and Transformer-based Models based on Literature Review

Criteria	Traditional (GMM-HMM)	Modern (DNN, RNN, CNN)	Transformers Based Models
Scalability	Low	Moderate	High, designed for multilingual and diverse inputs
Contextual Understanding	Poor	Moderate to High	High, leveraging large-scale pretraining datasets
Adaptability to Dialects	Low	Moderate	High, particularly with wav2vec 2.0 and CHIRP
Computational Efficiency	Low	Moderate	Moderate to High (Whisper and CHIRP optimized)

3.4.2 Chosen Models

For this study, three transformer-based models have been selected based on their state-of-the-art technology and performance in speech recognition. These models also has been selected based on their compatibility with the research objectives. The first selected model is Whisper from OpenAI for its ability to perform very well in multilingual and multitask environments using large-scale weak supervision (Radford et al., 2023). The architecture that based on simple encoder-decoder transformers has increase its performance transcription across various languages. The whisper model has been trained by using over 680,000 hours of audio. This makes it a very suitable model for addressing the issue of context-based syllable recognition and complex script systems in Japanese ASR (Bajo et al., 2024).

The second model that has been selected is Meta's wav2vec 2.0. This model has been selected because of its innovative self-supervised learning approach where only small amount of labelled data is needed to train this model (Baevski et al., 2020). It also has the ability to learn speech representations directly from raw audio, followed by fine-tuning on smaller labelled datasets, makes it particularly suitable for handling low-resource languages and diverse dialects. Because of that, wav2vec is very suitable to handle regional dialects and informal speech in Japanese language (Miwa & Kai, 2023).

The third selected model is CHIRP that build based on Universal Speech Model was chosen for its emphasis on multilingual scalability. This model has been trained on an extensive dataset encompassing 300 languages. Its BEST-RQ pretraining framework and innovative chunk-wise attention mechanism offer significant advantages in processing long audio sequences and handling diverse linguistic inputs (Zhang et al., 2023). Its superior performance in low-resource languages positions it as a strong contender for addressing Japanese speech recognition challenges, including phonetic ambiguities and dialectical diversity.

3.5 Model Testing and Evaluation

3.5.1 Testing Environment

The model testing will be using the Hugging Face platform, which is a widely used and versatile framework for deploying and testing Machine Learning models. Hugging Face provides out of the box integration with the chosen speech recognition models. This is the example of the code to load and run the Whisper model from Hugging Face by using python pytorch and transformers library.

Listing 3.3: Python code to load Whisper model from Hugging Face

```
import torch
from transformers import pipeline

whisper = pipeline("automatic-speech-recognition",\
    model="openai whisper-large-v3")
transcription = whisper("Sample_audio.mp3",\
    chunk_length_s=30)
print(transcription["text"][:500])
```

To provide better and more consistent evaluations, the testing environments for all models will be standardized. The sample will be prepared using the same preprocessed method for audio files which are sampled at 16 kHz standard. This will make sure all the input data will be compatible with the models then the test will be conducted in the same environment to provide identical hardware and software configurations, so the results of the models can be compared.

3.5.2 Performance Metrics

To evaluate the performance of the selected speech recognition models, these key metrics will be used:

1. Word Error Rate: Measures the accuracy of transcriptions by calculating the percentage of words that incorrectly transcribed. This is a critical metric for assessing the overall precision of the models.

$$\text{WER} = \frac{S+I+D}{N} \times 100\%,$$

where:

- S = Number of substitutions
- I = Number of insertions
- D = Number of deletions
- N = Total number of words in the **reference** transcription

2. Transcription Latency: Measures the time taken by each model to transcribe audio input, providing insight into their suitability for real-time applications.

$$\text{Latency}_i = t_{\text{end}}(i) - t_{\text{start}}(i),$$

where:

- $t_{\text{start}}(i)$ = Timestamp when the model begins receiving or processing the i-th audio.
- $t_{\text{end}}(i)$ = Timestamp when the final transcription for the i-th audio is produced.

To compute the average latency over M utterances:

$$\text{Average Latency} = \frac{1}{M} \sum_{i=1}^{M} \left(t_{\text{end}}(i) - t_{\text{start}}(i) \right).$$

3. Handling of Formal vs. Informal Language: Evaluates how well the models perform across different linguistic contexts, including formal speech and infor-

mal, dialectal speech.

$$\text{WER}_{\text{informal}} = \frac{S_i + I_i + D_i}{N_i} \times 100\%,$$

where:

- S_i, I_i, D_i = Substitutions, insertions, and deletions within the informal subset.
- N_i = Total number of reference words in the informal subset.

3.5.3 Test Procedure

The following step-by-step procedure was implemented to evaluate the models:

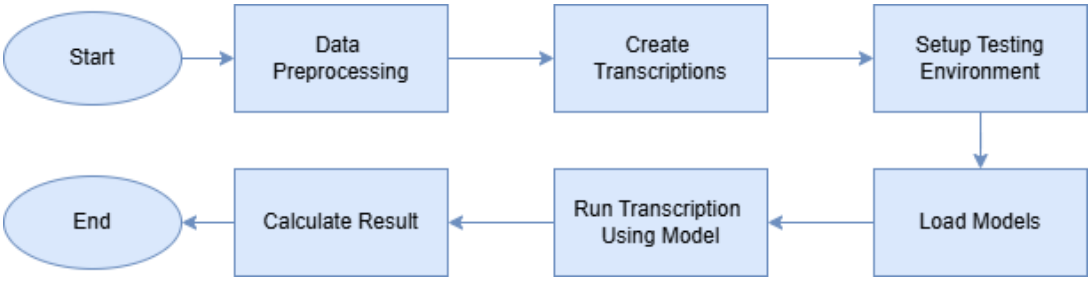

Figure 3.2 Testing procedure

In order to make sure the audio input file to be consistence across the dataset, the model evaluation will be start by pre-processing all the input data. This will make sure that the input data is compatible with the targeted models. Then, the pre-processed data that did not have transcription ready will be transcribe manually. These data is usually come from Ted Talk Youtube dataset because all data from COJADS has its transcription ready.

After the input data is ready, the preparation for testing environment will be carried out. The testing environment will be using model that prepared by Hugging Face as the platform comes with controlled configuration. Then the selected model will be load from the Hugging Face platform input data will be fed into the models one by one automatically. After that, the output transcription will be compared with the benchmark transcription to evaluate the accuracy metric and to observe each model ability.

3.6 Challenges and Limitations

One of the major challenges in this study is the availability of high quality dataset that has comes with annotation for Japanese speech recognition. Although the dataset like TED Talks YouTube and the Corpus of COJADS gives a valuable resources, they may not fully cover all the different aspect in the linguistic diversity in Japanese. Not only that, the variations in recording quality and noise levels within the datasets may also introduce inconsistencies that may affect the models' performance evaluation.

Another limitation during carried out this study is the bias that may be occur during the dataset selection process. Dataset from Ted Talk Youtube may only capture the formal Japanese language without having enough representation for daily use of the Japanese language. The Corpus of COJADS dataset also may only be capture the six most major dialects in Japanese while ignoring other dialects as there is not enough data available to be used in this test. Because of this bias, it could temper the evaluation results by favoring models better suited to the specific characteristics of the datasets.

3.7 Ethical Considerations

In this study, the ethical challenges that may be rise is on data privacy, consent and the fairness when evaluating the models. The dataset that has been used in the study contain publicly available speech recordings and there is no private or sensitive information is disclosed. Apart from that, the dataset from Ted Talk Youtube and the COJADS is widely available and can be obtain easily thus did not require individual consent for research purposes. This study will only be using the data for evaluating the performance of speech recognition models rather than analyzing the content of the recordings, reducing potential privacy concerns.

3.8 Summary

In this chapter, a clear research design was laid out to compare three ASR models on Japanese speech. Formal (TED Talks) and informal (COJADS) datasets were chosen for linguistic variety, and consistent preprocessing steps were described.

The reasoning for selecting Whisper, wav2vec 2.0, and CHIRP USM was explained, followed by details on how testing will be conducted in a standardized environment to measure WER and transcription latency. Lastly, challenges in dataset availability, biases, and ethical considerations around data privacy were also addressed in this chapter.

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