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Development of a System for Translating Frequently Used Turkish Sign Language Words into Text for Deaf or Hard of Hearing Individuals

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Deaf or Hard of Hearing individuals,
Turkish Sign Language,
Text Conversion

Abstract: Communication involves exchanging emotions, thoughts, and information through verbal and non-verbal methods. Sign language, used by individuals who are Deaf or Hard of Hearing, relies on gestures and facial expressions. It is not universal; different countries have distinct versions. Each sign consists of three components: hand shape, position, and movement.This study develops a system to recognize and convert frequently used Turkish Sign Language (TSL) words into text. Using an image processing algorithm and the YOLOv8 machine learning model, the system detects and translates 20 common words collected from 12 participants. The model achieved a 99.4% accuracy rate, proving its effectiveness in real-world conditions.This system enhances daily interactions for Deaf or Hard of Hearing individuals, providing an accessible communication tool. The findings may contribute to assistive technology, improving inclusivity and facilitating smoother interactions in various social settings.

İşitme Engellilere Yönelik Türk İşaret Dilinin En Çok Kullanılan Kelimelerini Yazıya Çeviren Sistem Tasarımı

Anahtar Kelimeler
İletişim,
İşitme engelliler,
Türk işaret dili,
Yazıya dönüştürme

Öz: İletişim, bireyler arasında duyguların, düşüncelerin ve bilgilerin sözlü ve sözsüz yöntemlerle aktarılmasını içerir. İşaret dili, işitme engelli veya sağır bireyler tarafından kullanılan ve jestler ile yüz ifadelerine dayanan bir iletişim biçimidir. Evrensel bir sistem olmayıp, farklı ülkelerde farklı versiyonları bulunmaktadır. Her işaret, el şekli, el konumu ve el hareketi olmak üzere üç bileşenden oluşur. Bu çalışma, yaygın olarak kullanılan Türk İşaret Dili (TİD) kelimelerini tanıyarak metne dönüştüren bir sistem geliştirmektedir. Görüntü işleme algoritması ve YOLOv8 makine öğrenme modeli kullanılarak, 12 katılımcıdan toplanan 20 temel kelimenin tespiti ve çevirisi gerçekleştirilmiştir. Model, 99.4% doğruluk oranına ulaşarak gerçek dünya koşullarında etkinliğini kanıtlamıştır. Bu sistem, işitme engelli bireyler için günlük etkileşimleri kolaylaştırarak erişilebilir bir iletişim aracı sunmaktadır. Bulguların, destekleyici teknolojilere katkı sağlayarak kapsayıcılığını artıracağı ve bireylerin sosyal etkileşimlerini iyileştireceği ön görülmektedir

1. Introduction

The Latin word for communication is "communico", which means "to share, to associate". Communication is one of the most important and basic needs of human beings since the creation of humankind. The pictures drawn on cave walls, the sounds made by African natives, the smoke emitted by Indians by lighting a fire are primitive methods used by humans to communicate [1].

Communication, which refers to the exchange of feelings, thoughts, information and news between people, takes place in various forms and methods. This complex process involves the mutual exchange of information and emotions and is not limited to words. It also aims to establish cross-cultural connections, express emotions and share thoughts. Communication is not only the exchange of information, but also a profound form of interaction that enables people to

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connect, understand and empathize with each other. It can basically be divided into two main groups: verbal and non-verbal communication.

Verbal communication refers to the type of communication that is constantly established in daily life. Verbal communication, which takes place through speech and language use between people, is used to express feelings, thoughts and information. Table 1 shows the most commonly used words in daily life.

Non-verbal communication is a form of communication that does not use words, such as body language, gestures and facial expressions, but is effective in conveying feelings, intentions and thoughts. Non-verbal communication is as important as verbal communication and can sometimes mean more than words. The subtleties of body language, the meanings of gestures and the emotions expressed by facial expressions can add depth to communication. Communication is the basis of interaction between people.

Using verbal and non-verbal means of communication effectively can increase understanding, strengthen relationships and contribute to mutual understanding. The most preferred type of communication between people is verbal communication. However, individuals with hearing impairment cannot fully utilize verbal communication. Hearing impairment can be congenital or acquired as a result of factors such as illness or accident. Individuals with hearing loss who use hearing aids or cochlear implants generally prefer auditory-verbal communication, while individuals with hearing loss who are diagnosed late and therefore cannot develop speaking skills tend to use sign language [2].

This study focuses on understanding the difficulties in the daily lives of hearing impaired individuals and developing solutions to overcome these difficulties. Since hearing impairment manifests itself in daily interactions as well as communication barriers in social interactions, the aim of this study is to provide a more effective communication experience for hearing impaired individuals by overcoming these barriers. Another goal of this study is to facilitate the communication of individuals with hearing impairment with the society and to support their social lives. The basis of this research is a system that can recognize the most frequently used words of sign language. This system aims to detect the words of sign language through an image processing algorithm and convert them into text. In this way, hearing impaired individuals can communicate effectively and interact more easily with their environment.

Table 1. Common words that used in Turkish Language (TR-EN)

Anne (Mother)	Dinlenmek (Resting)	İyi (Good)	Saat (Clock)	Yarın (Tomorrow)
Araba (Car)	Dost (Mate)	Kardeş (Brother)	Sabah (Morning)	Yemek (Eating)
Arkadaş (Friend)	Dur (Stop)	Kısa (Short)	Sen (You)	
Az (Less)	Ev (Home)	Kötü (Bad)	Sonra (After)	
Baba (Father)	Evet (Yes)	Merhaba (Hello)	Şimdi (Now)	
Bebek (Baby)	Fazla (Much)	Nasıl? (How?)	Tamam (Okey)	
Ben (Me)	Gece (Night)	Nasılsın? (How are you?)	Telefon (Phone)	
Bir (One)	Geri (Back)	Ne zaman? (When?)	Teşekkürler (Thanks)	
Bugün (Today)	Hayır (No)	Nerede? (Where?)	Tuvalet (Toilet)	
Çay (Tea)	İçmek (Drinking)	Önce (Before)	Türkçe (Turkish)	
Destek (Support)	İleri (forward)	Özür dilemek (Sorry)	Uzun (Long)	
Dikkat (Attention)	İletişim (Communication)	Para (Money)	Yardım (Help)	

2. Material and Method

Under this heading, we will first refer to some previous studies. Then, after providing a general overview of the study, we will discuss the processes step by step.

2.1. Related work

The first studies for image processing-based recognition of sign languages were carried out in the mid-1990s. In one of these studies, Starner worked on sign language recognition using a simple camera. The hands were segmented in the images taken from the motion sensor and feature vectors containing the positions of the hands were generated with Markov models, thus performing sign recognition. In this study, a success rate of over 90% was achieved for 40 words. Starner also presented a wearable computer capable of sign language recognition. In this study, a camera placed on a hat was used to recognize images of hand gestures using features such as shape and position. For performance measurement, a 40-word sign data set of American Sign Language (ASL) was used and a 99% success rate was achieved [3].

In order to facilitate the communication of the hearing and speech impaired, the study conducted by Tonjih Tazalli et al. focused on the understanding of sign language at the word level and stated that a database should be created to recognise words in Bangla sign language. While most existing studies have focussed on alphabets or numerical expressions, the focus of this study was on Bangla word signs. Sign language recognition usually involves isolated and continuous scenarios. This study focused on the isolated scenario, i.e. only one sign language word was recognised in each video. A video classification model was developed using technologies such as PyTorch and YOLOv5. An accuracy rate of 76.29% was achieved on the training dataset and 51.44% on the test dataset [4].

In the study titled "Turkish Sign Language Word Translator with Microcontroller Systems", it is aimed to facilitate communication between speech impaired individuals and the society. In the proposed method, microcontroller (Arduino), display unit (LCD Panel) and flex, acceleration and gyro sensors are used. A special glove was developed for the modeling process of the words. Thanks to the sign language interpreter glove, it is aimed to provide communication between disabled and non-disabled individuals. When a disabled person shows the word in sign language by wearing the sign language translator glove, the data from the five flex, acceleration and gyro sensors on the glove are transferred to the microcontroller. Based on this data, the microcontroller determined the meaning of the sign and displayed it in written form on the display unit. Turkish sign language was used in the study. In order to determine the meaning of a sign language gesture, eleven data obtained by performing selected sign language gestures using gloves were recorded. These data obtained for each sign language gesture were used in the program running on the microcontroller to classify the signs [5].

The study conducted by Kustiawanto Halim et al., The Sign Language System for Bahasa Indonesia, called Sistem Isyarat Bahasa Indonesia (SIBI), follows the grammatical structure of Indonesian, which has made it a unique and complex system. SIBI has enabled the translation of the alphabet, root words and numbers into text. Current research is focused on recognizing reflective words, which includes combinations of prefixes, suffixes and suffixes of root words. Root words were separated and processed with minimal feature sets. SIBI includes time dependencies in the sequence data, so Long Short Term Memory (LSTM) was chosen as the machine learning model. Feature sets based on inflected word movements in SIBI were used as input. TensorFlow was used so that the model can be easily deployed on various devices. The best results were obtained using the 2-layer LSTM with 96.15% accuracy for root words (nominative), while the same model achieved an accuracy score of 78.38% for inflected words. However, the model struggled to correctly recognize prefixes and suffixes [6].

In the work carried out by Luis A. et al. an intelligent system for translating sign language into text is proposed. The proposed approach consists of hardware and software components. The hardware consists of a flexible polyester-nylon glove equipped with contact and inertial sensors. The software consists of a classification algorithm based on k-nearest nearest neighbours (k-NN), decision trees (DT) and dynamic time warping (DTW) algorithms. The proposed system was able to classify certain gesture patterns by recognising static and dynamic gestures. The system was tested for the translation of 61 letters, numbers and words from Ecuadorian sign language with a classification accuracy of 91.55%. This result is considered as a significant improvement compared to previous studies [7].

A study conducted by Jose L. et al. discussed an approach to capturing isolated gestures of American Sign Language and translating them into oral and written words. The general sign recognizer was tested using a subset of 30 single-handed characters in the American Sign Language Dictionary and achieved 98% accuracy. The system has proven to be scalable: when the dictionary is extended to 176 characters and tested without re-training, the accuracy is 95%. This represents an improvement over classification based on hidden Markov models (HMMs) and neural networks (NNs) [8].

Karaca developed an application that simulates Turkish content in Turkish Sign Language (TSL) using a 3D virtual model. Signs were represented by positional and/or angular changes at the joint points of the model. The curricula of the Primary School for the Deaf were examined and a data set with three compilations was created for use in the study. The first corpus contained 400 words for 21 themes in the first grade of the TSL course. The second corpus included 130 sentences for 9 themes for the second grade of the same course. The third corpus included 100 sentences for 4 themes for the Turkish course. In addition to the content in the corpora, the developed application also includes TSL-specific elements such as hand shapes and non-hand signs and interactive translation modules. There are two phases in the application: natural language processing and Turkish Sign Language (TSL) simulation. Intermediate texts of sentences were obtained before simulation with the rules determined based on natural language processing analysis. The intermediate texts were converted into TSL text on the application screen and simulated. In addition to the data obtained as a result of the analysis of corpora with natural language processing techniques, data on TSL, signs, and model joint points and hand movements used in sign representations are presented in detail [9].

Much research in the field of sign language aims to improve the quality of life of hearing impaired individuals. In this context, our current study focuses on the analysis of Turkish Sign Language (TSL) vocabulary. Previous studies on Turkish Sign Language (TSL) such as "Turkish Sign Language Translation" [10], "Turkish Sign Language Review: Communication and Grammar" [11], "The Language of Silence: Observations on Turkish Sign Language" [12], "A Study on Classifiers in Turkish Sign Language" [13] and "The Historical Adventure of Sign Language and Turkish Sign Language" [14], but there is no study on the analysis of Turkish words and transcription of these words in the literature.

The aim of this study is to convert the correspondence of these words into real-time text with a high degree of accuracy, by selecting Turkish words that are commonly used in everyday life. This transformation has ensured the effective translation of the sign language equivalents of the most common words in the TSL, using image processing techniques. The stages of this work include data set creation, data set classification, data sets training, algorithm creation using the model obtained, interface design, and system integration.

2.2. Overview

This section describes the headings on which the work was carried out, as shown in Figure 1. The titles describe how to create a data set, classify and train data sets, build algorithms based on trained models, and design a user-friendly interface.

It has identified what characteristics the study needs to enable people with hearing impairments to communicate more effectively. This includes defining functional properties such as sign language recognition, sign perception, text conversion, real-time translation. It is important to create an easy-to-use, understandable and accessible interface for users. The choice of colors, fonts, icons and menus will be taken into account for the availability and comprehensibility of hearing impaired persons.

In this context, the study will be designed in QtDesigner environment. While determining the design needs, the study will aim to provide a user-oriented and functional solution, improve the daily life of hearing impaired individuals and provide them with a more effective communication experience. The focus is on understanding the communication difficulties of hearing impaired individuals in their daily lives and improving these experiences. In this framework, a user-centered and functional approach was adopted in determining the design needs, thus better understanding the needs of hearing impaired individuals and increasing the effectiveness of the study. Experiments and feedback during the prototype phase are crucial for the development of the system and the elimination of deficiencies. User feedback was taken into consideration to help the system better meet user needs.

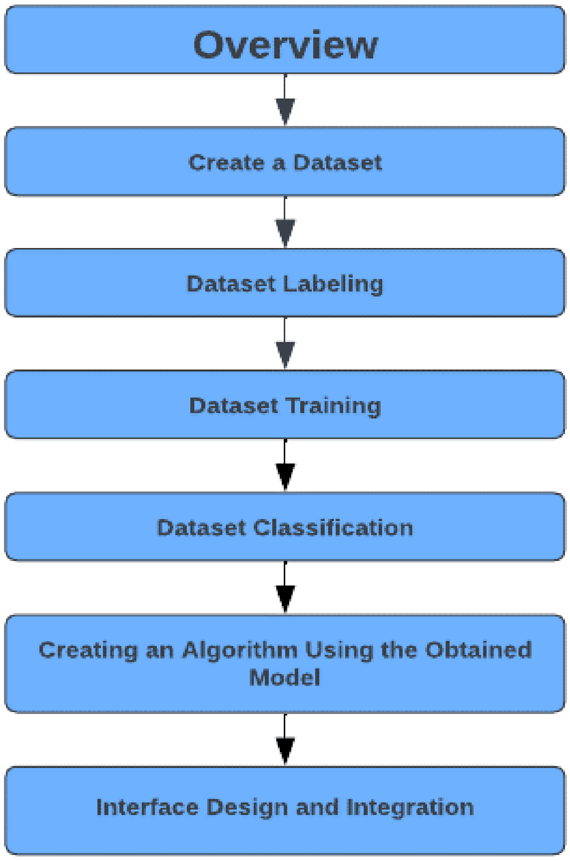
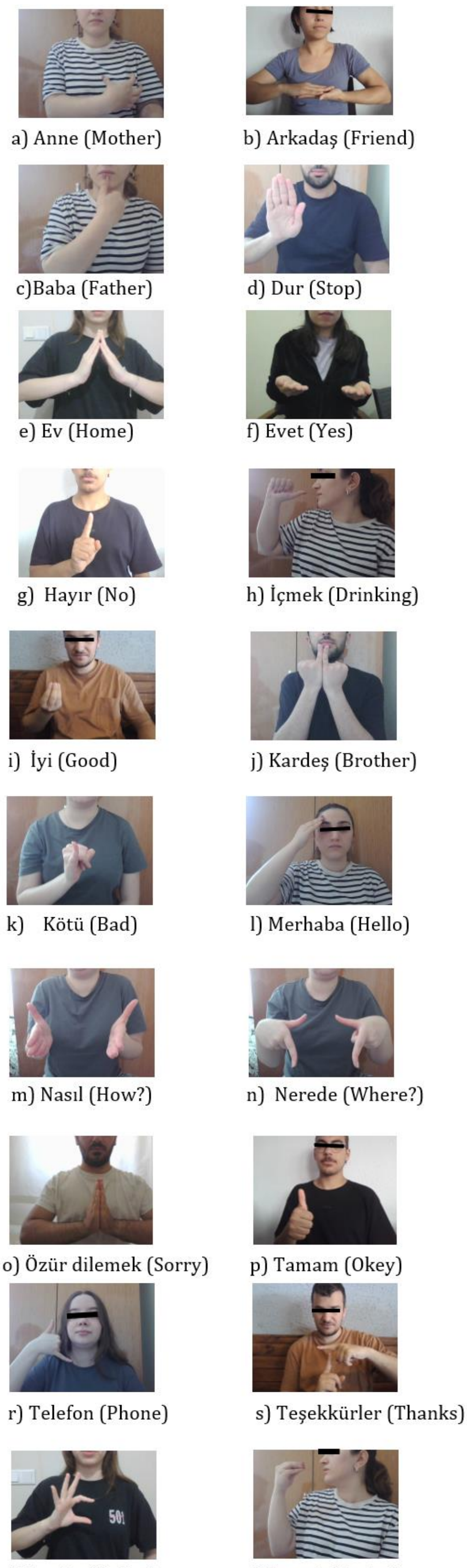


Figure 1. Block diagram of the study

2.3. Dataset

Turkish Sign Language consists of 2.000 words/concepts in its current form. It is formed by the use of both hands and their positions. As a first priority, the study area was determined by selecting the 20 most frequently used words/concepts in daily life within the scope of creating a data set. In this context, data ranging from 450 to 550 were collected from 1 person for each word, 12 people in total. Ethics committee approval was obtained for the data collection steps for this study (E-26428519-050.99-133710). The strength of the data set was ensured by creating background diversity [15,16]. The data of the collected words/concepts are shown in the Figure 2 below.

After selecting the words/concepts to be used, data set creation methods were discussed. Basically, an algorithm containing the requirements was created. The algorithm was designed to be usable in many environments (Google Colab, local computer, Roboflow, etc.). This usability can be explained by the fact that the images are saved in .txt format along with their labels. This method has added flexibility to the work. Figure 3 shows the data set algorithm. As a result of the designed algorithm, the data set creation code was written in Python. Running the code produced data with a resolution of 640x480.



a) Anne (Mother) b) Arkadaş (Friend)
c)Baba (Father) d) Dur (Stop)
e) Ev (Home) f) Evet (Yes)
g) Hayır (No) h) İçmek (Drinking)
i) İyi (Good) j) Kardeş (Brother)
k) Kötü (Bad) l) Merhaba (Hello)
m) Nasıl (How?) n) Nerede (Where?)
o) Özür dilemek (Sorry) p) Tamam (Okey)
r) Telefon (Phone) s) Teşekkürler (Thanks)
t) Tuvalet (Toilet) u) Yemek (Eating)

Figure 2. Collected words for the study

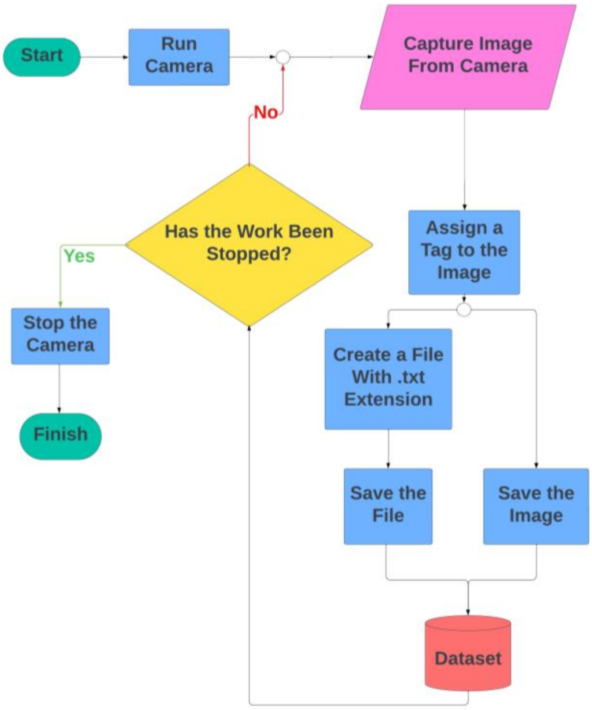


Figure 3. Flowchart of the data collection

2.4. Labeling of the dataset

Evaluations were conducted between Google Colab, Roboflow, and local computer options to train the created data set. Pit detection using Roboflow Convolutional Neural Networks [17] was performed by D. Deepa, A. Sivasangari, Rahul Roonwal, and Rajeev Nayan in 2023 [18], Vasudevan, H. Matuck et al. in 2024 [19], and the implementation of an enhanced security system using the YoloV8 model via RoboFlow by Pavithra, M. Brucal et al. in 2024 [20], The high accuracy of these studies and the recognition study conducted by Guilherme Rodrigues Matucks et al. in 2023 [21] led to the real-time detection of objects by Roboflow. Additionally, its suitability for teamwork via the cloud, ease of augmentation application, and ability to present training outputs in graphical form provide significant convenience in processes. In this regard, it was decided to provide training through Roboflow. The data was then labelled in the Roboflow environment as shown in Figure 4. The labels created during the data set creation phase were retained for future use.

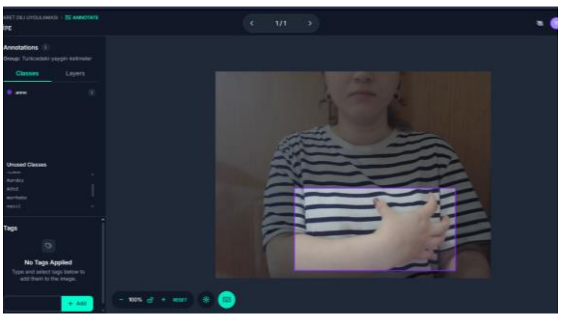


Figure 4. Labeling process of the study

The words/concepts labelled in the Roboflow environment were subjected to data partitioning. The data was divided into three data sets: training, validation, and testing. The training data set is the data set that contains the most data and is used to perform the basic training of the model. This data set is used to test model algorithms and select the best algorithm. The validation dataset is used to evaluate the results obtained during the model's learning process. The test dataset tests how the model performs in the real world. In this process, the learned model is used on the training dataset, and predictions are compared with real data. As a result, the model's performance is evaluated using accuracy metrics such as the accuracy rate.

The efficiency of our dataset is divided by the globally accepted ratio of 70% Training, 20% Validation and 10% Testing as indicated in Figure 5.

"Box Loss" is a loss function used in object detection and segmentation tasks. This function is especially used in pixel-based segmentation algorithms.

Figure 5. Training, Validation and Testing separation

In the final stage before training the dataset, various augmentations were added. These included a 15% greyscale application, blurring up to 2.5 pixels, and artificial noise such as saturation between -25% and +25%. This noise focuses particularly on colour and blurring factors. Colour noise aims to diversify the dataset by randomly changing the colour values of pixels. This allows the model to better adapt to different colour tones and lighting conditions. Blur noise simulates various real-world conditions by reducing the sharpness of images. This ensures that the model performs well even with blurry or low-quality images. As a result, these artificial noises enhance the power of the dataset, making the model more generalised, better adapted to real-world data, and preventing potential overfitting [22].

The training of the model will be done with 300 repetitions (epochs) in a way that the accuracy of the model will be strong [23, 24]. In this way, it will be seen that the "Box Loss" in Figure 6, "Class Loss" in Figure 7 and "Object Loss" in Figure 8 are significantly improved.

"Box Loss" is a loss function used in object detection and segmentation tasks. This function is especially used in pixel-based segmentation algorithms.

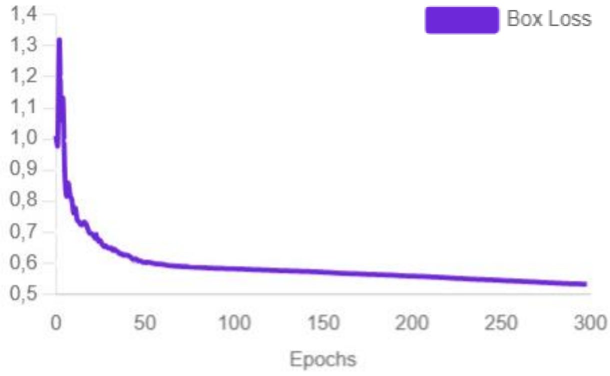


Figure 6. Box Loss graph

The term "Class Loss" is used to improve the performance of object detection and classification models. This function evaluates the difference between the class labels predicted by the model and the actual class labels.

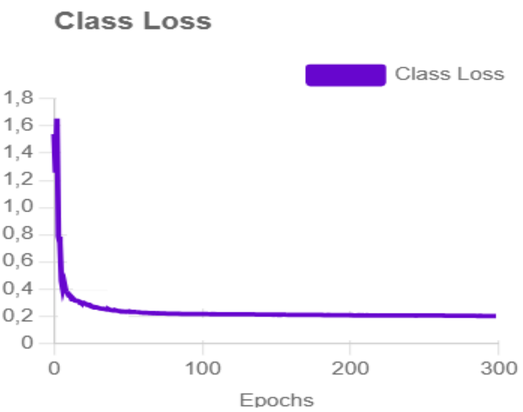


Figure 7. Class Loss graph

"Object Loss" is a loss function used in object detection and partitioning models. This function measures the difference between the model's predicted bounding boxes and the actual bounding boxes. The purpose of object loss is to improve object detection and partitioning performance by directing models to predict more accurate bounding boxes.

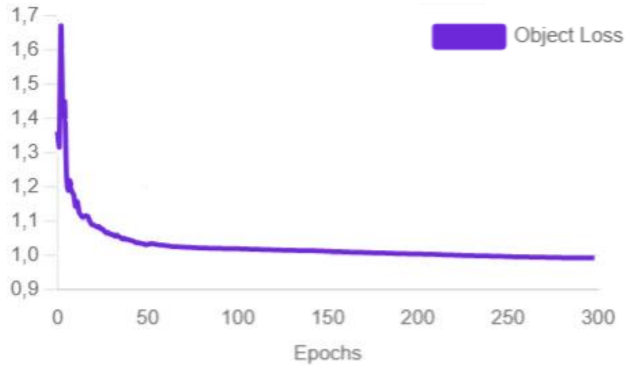


Figure 8. Object Loss graph

As a result of this improvement, the mAP (average of accuracy measurement in model classes), Precision (how often model estimates are correct) and Recall (percentage of labels successfully defined) values will be calculated at higher values as shown in Figure 9 and Figure 10.

Figure 9. Values of mAP, Precision and Recall

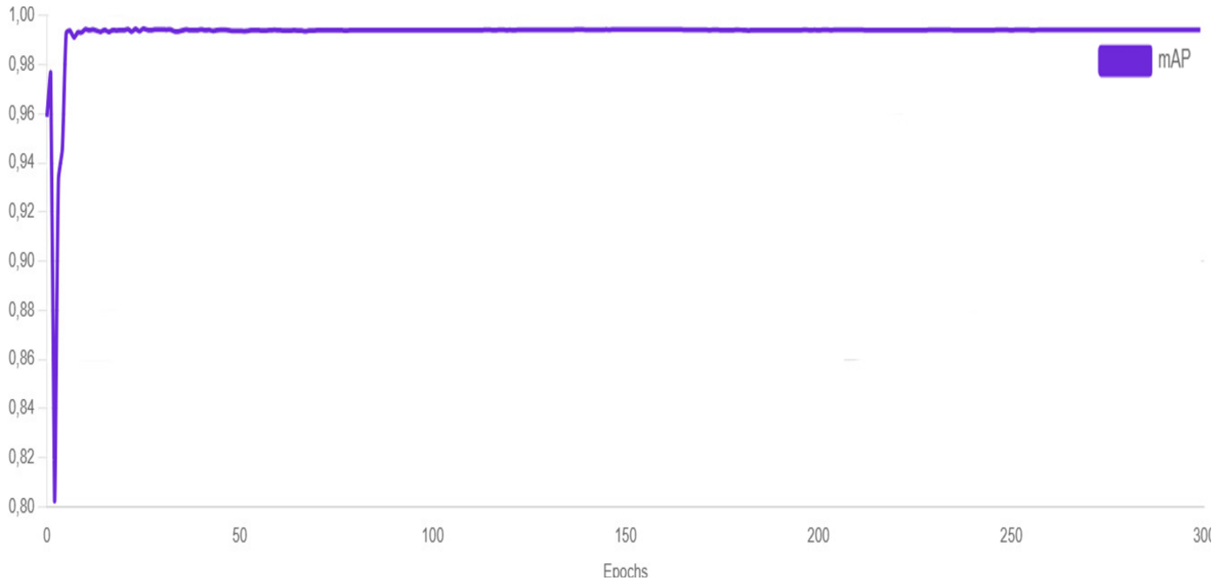


Figure 10. mAP graph

2.5. Algorithm of the designed model

After the training was provided through Roboflow, the stage of using the obtained model was reached. The obtained model was used with a code set written in Python programming language on the local computer. Before creating a code, it is necessary to focus on the requirements and requirements of the programme. In this context, an algorithm should be created. Figure

11 shows the algorithm in question. After the algorithm was obtained, a code set was created in Python programming language based on this algorithm. Visiual Studio code environment was found suitable for this. Roboflow library, OpenCV, cvzone and other necessary libraries and modules were added in order to use the model obtained through Roboflow on the local computer.

2.6. Designing and integration of the interface

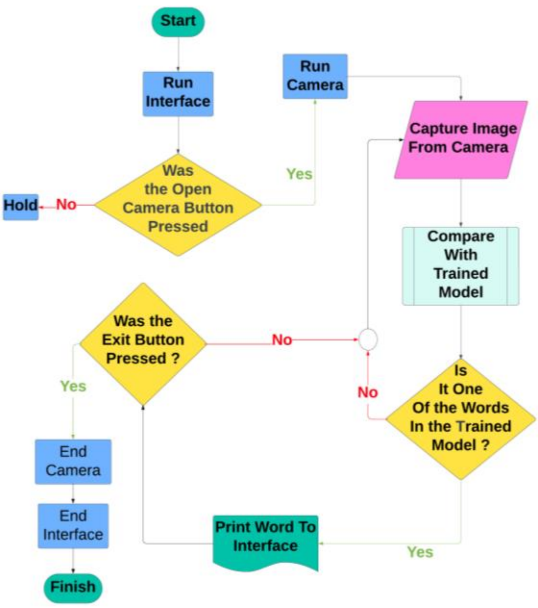


Figure 11. Flowchart of the designed model

The interface has been implemented as a simple and understandable interface in the design phase. Qt Designer was chosen for the design of the interface, which was described in a study by Nabijonovich S. B. et al. in 2024, because it had a user-friendly interface, based on a quick and efficient design and easy integration into the software language used [25]. In this context, the Qt Designer environment has begun to design an interface, as shown in Figure 12 the interface saved in ui format so that it can be integrated into our system written in the Python programming language converted to the py extension. On the interface, the buttons to turn on and exit the camera are dynamic. The translated py file has been revised and integrated into the code.

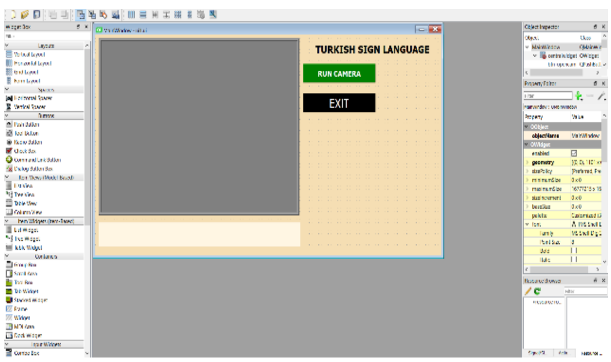


Figure 12. Designing of the interface

3. Results

In order for the system to work, the data set must first be created. For this purpose, a data set with a code written in the Pyhton programming language has been created. Once the data set is created, the data must be classified and labelled. For this purpose, data has been prepared for training in the Roboflow environment. The training of the data set, which has been prepared for training, has begun in the Roboflow environment as the COCO data set. At the end of the training, the parameters specified in Figure 13 were achieved.

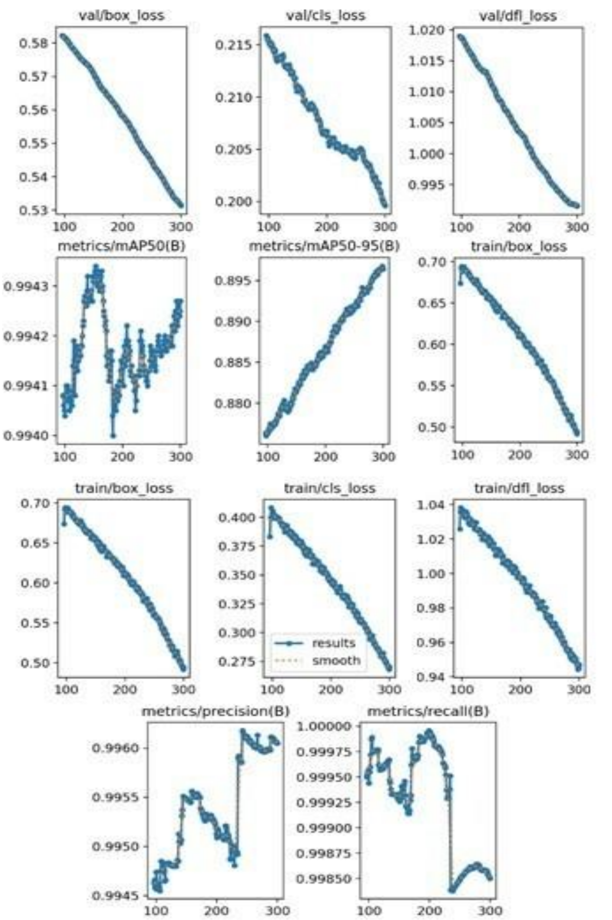
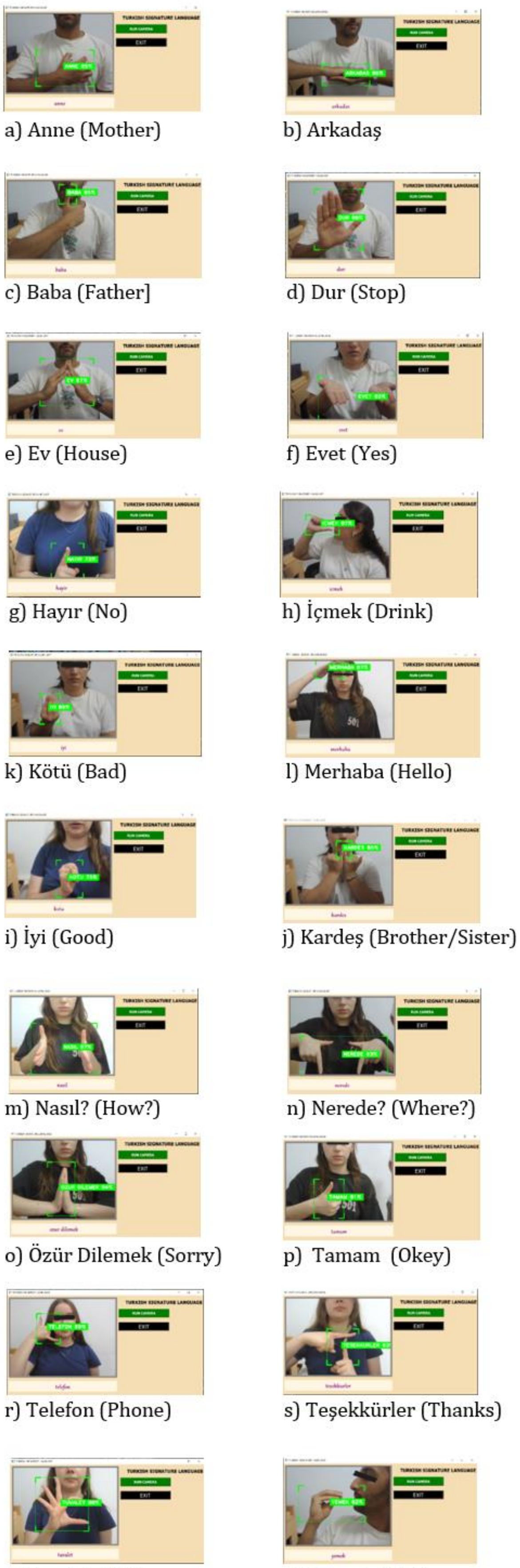


Figure 13. Parameters of training process

The trained model obtained at the end of the training was written in a main code in Python programming language, which takes images from the camera and undergoes the comparison process, showing the word class at the highest accuracy. These processes resulted the design of a very functional and simple interface for the real user to access. In this context, the interface in the Qt Designer environment has been designed. The necessary format conversion process has been carried out so that the designed interface can be in integrated into the main code. It was subsequently tested, and the necessary locations were revised and the work was completed, as shown in Figure 14.



a) Anne (Mother) b) Arkadaş
c) Baba (Father] d) Dur (Stop)
e) Ev (House) f) Evet (Yes)
g) Hayır (No) h) İçmek (Drink)
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i) İyi (Good) j) Kardeş (Brother/Sister)
m) Nasıl? (How?) n) Nerede? (Where?)
o) Özür Dilemek (Sorry) p) Tamam (Okey)
r) Telefon (Phone) s) Teşekkürler (Thanks)
t) Tuvalet (WC) u) Yemek (Eat)

Figure 14. Testing of the system

4. Discussion and Conclusion

This study is focused on understanding and overcoming the challenges in the daily lives of hearing impaired individuals. Although there is limited literature on a system that translates the most frequently used words of Turkish Sign Language (TSL) in real-time, this study aims to fill this gap. In the study, data was collected from 12 individuals for 20 frequently used words/concepts in the TID alphabet and processed using Python programming language. The processed data was trained with the YOLOv8 machine learning algorithm in the Roboflow environment and a high success rate was achieved. The dataset was varied with different lighting conditions, backgrounds and camera angles to increase the model's adaptability to real-world conditions.

YOLOv10, which is likely to add greater accuracy and effectiveness, was not preferred because since it is a relatively new method and community support is still limited. In the study, the Roboflow environment was preferred by avoiding the physical difficulties of conducting local training. In this way, time spent before and during the training was saved. Since the study will ultimately serve a user in need, a simple interface was needed. Qt Designer, which offers high accessibility in this context, has been chosen. This preference has been granted a waiver the interface from visualizing by creating a Python code.

In this study, methods and tools that have proven themselves in terms of effectiveness and usefulness were used. As can be seen in Table 2, the accuracy rate in this study is quite high (99.4%) compared to other studies using YOLOv5. YOLOv8 has added high accuracy and effectiveness to this study. In studies using YOLOv5 as machine learning, the lowest accuracy rate was 73.4% in the study by Deepa et al., 76.29% in the study by Tonjih Tazalli et al. The highest accuracy rate was measured as 97.9% in the study conducted by Vasudevan et al. Kustiwanto and ark. have achieved accuracy rates of 78.38% and 96.15% using LTSM. In studies using YOLOv8 as machine learning, the lowest accuracy rate was 91% in the study by Matuck et al., 97.9% in the study by Vasudevan et al. and the highest accuracy rate was 98.9% in the study by Brucal et al. Çamlıbel et al. Using SST and FSST achieved 87% accuracy, while Pavithra et al. achieved 95.7% accuracy using RoboflowIn this study, using Roboflow and YOLOv8, which is better than other studies an accuracy rate of 99.4% was achieved. These results emphasize that the methods selected in this study are optimum compatible with each other.

This study focuses on understanding the challenges faced by hearing-impaired individuals in their daily lives and developing solutions to enhance their communication capabilities. By collecting data for 20 frequently used words and concepts in Turkish Sign Language (TSL) from 12 individuals, this research aims to provide a robust solution for real-time translation of TSL into text. The data was processed using Python and trained with the YOLOv8 machine learning algorithm in the Roboflow environment, achieving a high accuracy rate of 99.4%.

The dataset's diversity, achieved through varying lighting conditions, backgrounds, and camera angles, ensured the model's adaptability to real-world conditions. The study avoided using the newer YOLOv10 due to its limited community support, opting instead for the more established YOLOv8, which proved to be highly effective.

A user-friendly interface was designed using Qt Designer, emphasizing accessibility and ease of use. The interface, integrated with the trained model, allows for real-time translation of TSL into text, significantly improving communication for Deaf or Hard of Hearing individuals. This system not only addresses daily interaction challenges but also supports the social integration of hearing-impaired individuals by providing them with a reliable communication tool.

In summary, the developed system demonstrates high accuracy and practical utility, contributing to a better communication experience for hearing-impaired individuals and facilitating their interaction with the surrounding environment.

Table 2. Accuracy rates comparison between studies that uses YOLO

Authors	Methods	Accuracy
Deepa, D. et al. [15]	YOLOv5, CNN	73.4 %
Brucal, S. G. E. et al. [16]	YOLOv8, NMS	98.9%
Vasudevan, H. et al. [17]	YOLOv5, YOLOv8	97.9%
Camlibel, A., Karakaya, B., & Tanc, Y. H. [20]	SST, FSST	87%
Kustiawanto H., Erdefi Rakun [6] (Plain words)	LSTM	96.15%
Kustiawanto H.; Erdefi Rakun [6] (Inflected words)	LSTM	78.38%
Pavithra, M. et al. [18]	Roboflow	95.7%
Matuck, G. R. et al. [19]	YOLOv8	91%
Tonjih Tazalli et al. [4]	PyTorch, YOLOv5	76.29%
Current study	Roboflow, YOLOv8	99.4%

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Declaration of Ethical Code

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent was obtained from all the participants and ethics committee approval was obtained for the data collection steps for this study (E-26428519-050.99-133710). (E-26428519-050.99-133710).

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