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ANALYSIS OF RECOGNITION ALGORITHMS AND CONVOLUTIONAL NEURAL NETWORK FOR HAND GESTURE RECOGNITION IN KAZAKH SIGN LANGUAGE

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Abstract. The ever-growing interest in machine learning and neural networks is fueled by significant advancements in computational capabilities, enabling breakthroughs in object, sound, text, and other forms of data recognition. These advancements have paved the way for a more intuitive interaction between humans and machines, making such technologies accessible to a wider audience. Recent developments in computer vision, in particular, have led to the creation of sophisticated models capable of recognizing objects in images and videos. This same technology has been effectively adapted for hand gesture recognition, enabling applications in fields like human-computer interaction, robotics, and sign language interpretation. This paper explores some of the most popular hand gesture recognition models, with a particular focus on Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). These models differ in their methodologies, processing efficiency, and the volume of training data they require, offering various advantages and limitations depending on the application context. The core objective of this study is to provide an overview of diverse machine learning algorithms, delving deeply into their theoretical underpinnings, operational mechanisms, and comparative performance in terms of accuracy, training time, and data requirements. In addition, this work presents experimental results of sign language recognition in Kazakh, specifically using the dactyl alphabet. A detailed analysis is provided, accompanied by a comprehensive table that reports the accuracy of each recognized gesture. Real-time testing was conducted with individual hand gestures displayed in front of a camera, showcasing the effectiveness of the recognition system. Furthermore, the study incorporates an explanation of the mathematical foundations and logical structures underlying machine learning algorithms, illustrated through formulae, functional relationships, and flowcharts that depict the recognition process. By combining theoretical insights with practical experiments, this paper aims to contribute to the growing field of gesture recognition and its applications in accessible communication technologies.

Keywords: Hand gesture recognition, neural networks, algorithm, layer, CNN, SVM, YOLO

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ҚАЗАҚ ТІЛІНДЕ ҚОЛ ҚИМЫЛДАРЫН ТАНУ ҮШІН ТАНУ АЛГОРИТМДЕРІН ЖӘНЕ КОНВОЛЮЦИЯЛЫҚ НЕЙРОНДЫҚ ЖЕЛІНІ ТАЛДАУ

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Аннотация. Машиналық оқыту мен нейрондық желілерге деген қызығушылықтың үнемі артуы есептеу мүмкіндіктерінің айтарлықтай жетістіктерімен қамтамасыз етіледі, бұл объектілік, дыбыстық, мәтіндік және деректерді танудың басқа түрлерінде жетістіктерге жетуге мүмкіндік береді. Бұл жетістіктер адамдар мен машиналар арасындағы интуитивті өзара әрекеттесуге жол ашып, мұндай технологияларды кең аудиторияға қолжетімді етті. Компьютерлік көрудің соңғы жетістіктері, атап айтқанда, кескіндер мен бейнелердегі объектілерді тануға қабілетті күрделі модельдердің жасалуына әкелді. Дәл осы технология адам мен компьютердің өзара әрекеттесуі, робототехника және жестау тілін түсіндіру сияқты салаларда қолдануға мүмкіндік беретін қол қимылдарын тануға тиімді бейімделген. Бұл мақалада Конволюциялық Нейрондық Желілерге (Cnn) және Тірек Векторлық Машиналарға (Svm) ерекше назар аудара отырып, қол қимылдарын танудың ең танымал үлгілері қарастырылады. Бұл модельдер әдістемелерімен, өңдеу тиімділігімен және қажетті оқу деректерінің көлемімен ерекшеленеді, қолдану контекстіне байланысты әртүрлі артықшылықтар мен шектеулерді ұсынады. Бұл зерттеудің негізгі мақсаты-машиналық оқытудың әртүрлі алгоритмдеріне шолу жасау, олардың теориялық негіздерін, операциялық механизмдерін және салыстырмалы өнімділігін дәлдік, оқу уақыты және деректерге қойылатын талаптар тұрғысынан терең зерттеу. Сонымен қатар, бұл жұмыста дактил алфавитін қолдана отырып, signay тілін қазақ тілінде танудың эксперименттік нәтижелері келтірілген. Егжей-тегжейлі талдау әрбір танылған қимылдың дәлдігі туралы есеп беретін жан-жақты кестемен бірге беріледі. Нақты уақыттағы тестілеу тану жүйесінің тиімділігін көрсететін камера алдында көрсетілген жеке қол қимылдарымен жүргізілді. Сонымен қатар, зерттеу тану процесін бейнелейтін формулалар, функционалдық қатынастар және блок-схемалар арқылы суреттелген машиналық оқыту алгоритмдерінің негізінде жатқан математикалық негіздер мен логикалық құрылымдарды түсіндіруді қамтиды. Теориялық түсініктерді практикалық эксперименттермен үйлестіре отырып, бұл жұмыс қимылдарды танудың өсіп келе жатқан саласына және оны қолжетімді коммуникациялық технологияларда қолдануға үлес қосуға бағытталған.

Түйін сөздер: Қол қимылдарын тану, нейрондық желілер, алгоритм, қабат, CNN, SVM, YOLOД

әйексөз үшін: Н.Н. Лес, С.Б. Муханов, М.Т. Ипалакова, А.К. Мустафина. Казақ тілінде қол қимылдарын тану үшін тану алгоритмдерін және конволюциялық нейрондық желіні талдау//Халықаралық ақпараттық және коммуникациялық технологиялар журналы. 2025. Том. 6. № 24. 219–238 бет. (Ағыл). https://doi.org/10.54309/IJICT.2025.24.4.013.

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АНАЛИЗ АЛГОРИТМОВ РАСПОЗНАВАНИЯ И СВЕРТОЧНОЙ НЕЙРОННОЙ СЕТИ ДЛЯ РАСПОЗНАВАНИЯ ЖЕСТОВ РУК НА КАЗАХСКОМ ЯЗЫКЕ ЖЕСТОВ

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Аннотация. Постоянно растущий интерес к машинному обучению и нейронным сетям подогревается значительными достижениями в области вычислительных возможностей, позволяющими совершать прорывы в распознавании объектов, звука, текста и других форм данных. Эти достижения проложили путь к более интуитивному взаимодействию между людьми и машинами, сделав такие технологии доступными для более широкой аудитории. Последние разработки в области компьютерного зрения, в частности, привели к созданию сложных моделей, способных распознавать объекты на изображениях и видео. Эта же технология была эффективно адаптирована для распознавания жестов рук, что позволяет применять ее в таких областях, как взаимодействие человека и компьютера, робототехника и сурдоперевод. В этой статье рассматриваются некоторые из наиболее популярных моделей распознавания жестов рук, с особым акцентом на сверточные нейронные сети (CNN) и методы опорных векторов (SVM). Эти модели различаются по своим методологиям, эффективности обработки и объему требуемых обучающих данных, предлагая различные преимущества и ограничения в зависимости от контекста применения. Основная цель этого исследования - дать обзор различных алгоритмов машинного обучения, глубоко изучив их теоретические основы, операционные механизмы и сравнительную производительность с точки зрения точности, времени обучения и требований к данным. Кроме того, в этой работе представлены экспериментальные результаты распознавания языка жестов на казахском языке, в частности, с использованием дактильного алфавита. Приводится подробный анализ, сопровождаемый подробной таблицей, в которой сообщается о точности каждого распознанного жеста. Тестирование проводилось в режиме реального времени с использованием отдельных жестов рук, отображаемых перед камерой, что продемонстрировало эффективность системы распознавания. Кроме того, исследование включает в себя объяснение математических основ и логических структур, лежащих в основе алгоритмов машинного обучения, проиллюстрированных формулами, функциональными взаимосвязями и блок-схемами, которые описывают процесс распознавания. Сочетая теоретические идеи с практическими экспериментами, эта статья призвана внести вклад в растущую область распознавания жестов и их применения в доступных коммуникационных технологиях.

Ключевые слова: Распознавание жестов руками, нейронные сети, алгоритм, layer, CNN, SVM, YOLO

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Introduction

The Recognition of hand gestures (Gesture-recognition) is an important problem in the field of human-computer interaction. Hand gestures are used as a natural and intuitive way of communication between people and digital devices or systems. One of the most significant applications of this field is the recognition of sign language, which is used by people with hearing disabilities for communication. There are many different sign languages used around the world, and one of them is Kazakh Sign Language (KSL). KSL, like many other sign languages, is not widely studied, and there is a need for effective recognition systems to support its users. In recent years, recognition algorithms and deep learning methods, especially Convolutional Neural Networks (CNNs), have achieved significant success in computer vision and pattern recognition tasks. CNNs have shown state-of-the-art performance in various applications, including image classification, object detection, and hand gesture recognition, due to their ability to learn spatial features and hierarchical representations from data. This research paper aims to review and analyze different recognition algorithms and investigate the performance of CNN-based models for hand gesture recognition in Kazakh Sign Language. The goal is to use machine learning and computer vision techniques to improve the accuracy and efficiency of KSL recognition and contribute to the development of assistive technologies for people with hearing disabilities in Kazakhstan.

Review of related literature and problem statement

The state of the art in sign language recognition research is leaning towards deep learning-based systems. The recent works (Wang et al., 2020; Bilgin & Mutludogan, 2019) demonstrate CNN-based frameworks that can reach more than 90 % recognition accuracy on ASL and Turkish Sign Language datasets. However, research efforts dedicated to the problem of Kazakh Sign Language (KSL) recognition are still in their infancy. Kenshimov et al. (2021) and Mukhanov et al. (2023) have paved the way for this topic but used static images for the recognition task. This work extended the pipeline and demonstrated the real-time detection of hand gestures using YOLO and CNN.

The objective of this work will be to use various algorithms and machine learning methods within the convolutional neural network in order to identify certain gestures of the Kazakh sign language. Therefore, all these algorithms will be considered and tested, and their detailed description will be given. The convolutional neural network is typically used within deep learning for the image recognition set. The training of this network is based on machine learning. In addition to being an interconnected neural network, it is also what it is made of and what metrics it applies for predictions in pattern recognition -in our case, recognizing gestures in the Kazakh sign language. The current work will show the functions used in this convolutional network and the mathematical formulas for them. Convolutional neural networks are a type of deep neural network, which are specifically designed for processing images and videos. CNNs account for the spatial structure between pixels, and convolutional operations are applied to higher-order feature extraction from the data, from simple edges to more complex objects. CNNs have exhibited outstanding performance across many computer vision applications and have also demonstrated potential in other fields. Yann LeCun introduced CNNs in the 1980s, although they did not gain widespread use until the mid-2010s with the emergence of deep learning approaches and the availability of big datasets. CNNs are now widely employed in industry and academia and are anticipated to play an essential role in future technologies.

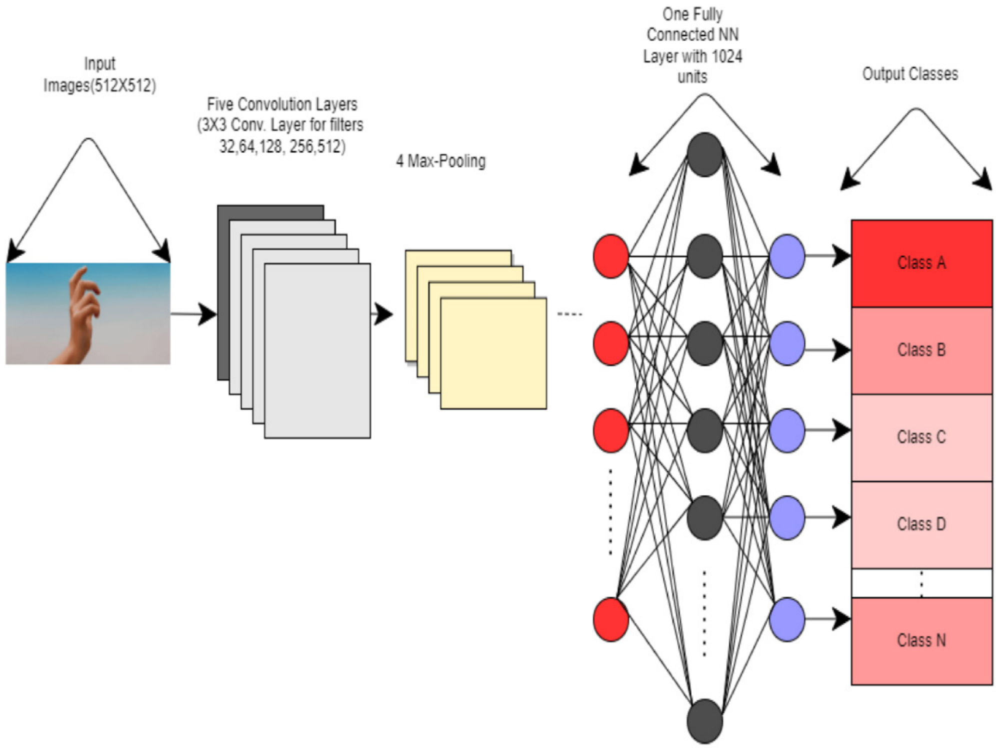


Fig. 1. An example of 2-D convolution

The mathematical operation of two functions (Convolutional operation):

$$[f * g](t) \equiv \int_0^t f(\tau)g(t-\tau)d\tau \quad (1)$$

where:

$[f * g](t) \equiv$ denotes the convolution of f and g;

The integral runs from 0 to t, integrating over the variable τ;

$f(\tau)$ and $g(t-\tau)$ are the function values at shifted arguments.

A layer will produce as many output feature maps as there are kernels in that layer. The relationship between the size of the output feature map and the input is that each kernel produces one feature map, which describes a single aspect of the input data. The complexity of the task and the data are what will determine the size and number of output feature maps. Each of these feature maps is a two-dimensional array for one filter that describes the presence of that filter in the input data. The values within these filters will be learned through backpropagation in order to get the greatest performance possible for the task at hand.

Alongside these kernels are channels that capture different aspects of the input data. The channels are two-dimensional arrays that each express a single characteristic of the input data. For instance, if the task were classifying images, then the input data might have distinct channels for edge data, textural data, color, and so on. It is the grouping of these channels and kernels that allow for the three key concepts in convolutional neural networks design. These include sparse interactions, sharing of parameters, and equivariant representations. Sparse interactions refers to how each output feature map is the result of convolution of a small kernel with only a few of the input feature maps, as opposed to all of the input feature maps. This also improves performance while also reducing the amount of parameters needed to represent the layer.

This is because one feature map produced by a kernel will have a similar effect; it is therefore sometimes known as parameter sharing. This works in such a way that each output feature map produced in a convolution layer is obtained by using the same kernel. This is akin to saying the weights in that kernel are shared between each of the output feature maps-the model does not learn the weights for each one separately. The immediate consequence of all this is a substantial reduction in the number of parameters needed to represent a model with significant improvements in its generalization performance.

Materials and methods

The CNN method in recognition problems

In this work, YOLO was only responsible for hand detection/localization while another CNN model oversaw classifying the detected gesture. For this, the segmented hand was used as an input for a gesture classifier that was trained separately. This pipeline was verified to be more flexible and allowed for independent fine-tuning of the detector and the classifier.

In this project, we used Convolutional Neural Networks to train machine learning algorithms in the recognition of hand gestures and Kazakh sign language. The results of recognition tested are in this work. However, it is necessary to introduce this network and how it works in pattern recognition. Convolutional Neural Networks (CNNs, in short) are a type of artificial neural network that is highly efficient at processing and analyzing visual data like images and videos. The basic structure of CNNs consists of an input data, for example an image, to layers of interconnected artificial neurons. Each neuron in each layer of the CNN is only connected to a small patch of the input; these patches are said to overlap, such that the totality of the input data is covered.

The convolution layer, which is one of the most important components of CNNs, makes use of learnable filters called kernels to extract features from the input data. The kernel is moved around the input in a process called convolution. It is worth noting that the kernel multiplies the values that correspond to the input at each location to get a set of feature maps. The number of output feature maps is determined by the number of kernels; this is because every kernel has one output feature map, which describes one particular feature of the input data. It is important to remember that this is the interaction of both these components: channels and kernels that enables sparse interactions, parameter sharing, and equivariant representations-the three important ideas in CNN design.

The choice of YOLO and CNN as recognition architectures was inspired by their mutual strengths. YOLO-based hand detector showed high accuracy and real-time performance while CNN is a state of the art in image classification tasks. Their integration into a single pipeline was found optimal for the task of KSL recognition since hand segmentation and dynamic motion localization are of great importance.

Support Vector Machine for hand gesture recognition

The system for the recognition of hand gestures that show letters is proposed in this paper. This system recognizes the hand gestures using biorthogonal wavelet transformation. The system for recognizing hand gestures is operated in several ways. Firstly, images are read and filtered to clean them from noise. After that, the system recognizes the edges of the images and calculate projections along certain directions by using the Radon transform. After that, the system applies biorthogonal wavelet transformation to these projections. For the recognition of hand gestures the system trains and tests SVM. Support Vector Machine (SVM) is a supervised learning algorithm that can be used for both classification and regression. The basic idea behind an SVM is to find a hyperplane that separates the data in the best possible way in a high-dimensional space. “Support vector” is the name for data points that are nearest to the decision boundary or hyperplane, which are essential to find out the optimal separation. This article present a comparative study of two SVM classificators: “Binary classification” and “Multiclass classification” for hand gesture recognition. In the paper we should like to say a few words about the research of the quality of binary classification. The most attractive properties of binary classification using SVM in hand gesture recognition is its power and efficiency. It has many benefits such as being a robust algorithm, achieving high accuracy, and having an interpretable model. Feature selection and hyperparameter tuning are critical for achieving optimal performance. On the other hand, as the research continues, the more resources of the computer there will be. In terms of application areas, SVMs can be used in various domains such as computer vision, image processing, robotics, and human-computer interaction. The application of binary classification using SVM in real-world scenarios will depend on the specific requirements and constraints of the application. It is also important to note that binary classification using SVM is just one of many algorithms and techniques that can be used for hand gesture recognition, and other methods may be more suitable depending on the application. We also should like to point out that a second classificator used in the experiment “Multiclass classification”. This classificator is not as effective as “Binary classification” and was used in experiment as an example.

Canny Edge Detection Algorithm is the method that system uses for the recognition of the image edges. This algorithm was chosen because this algorithm is the best among many benchmark algorithms. This algorithm finds the most appropriate edges by decreasing error rates, making possible the exact localization of edges, and only marking edges once in case of one edge in order to have a minimal response. The only filter that satisfies the requirements is the first derivative of Gaussian function and that filter can be approximated as.

$$w^T x + b = 0, \quad (2)$$

$$min_{w,b} \frac{1}{2}||w||, \quad (3)$$

$$y_i(w^T x_i + b) \geq 1, \forall_i, \quad (4)$$

where:

w is the weight vector that defines the hyperplane’s orientation, x is the feature vector for the input data, b is the bias term that shifts the decision boundary, y_i is the label of the ith data point (either +1 or -1), and x_i is the feature vector for the ith data point.

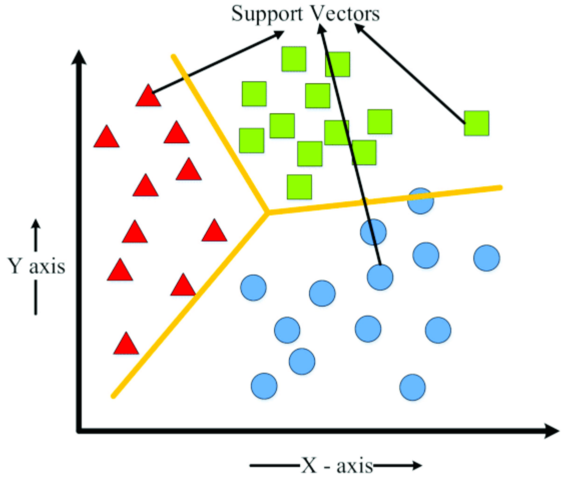


Fig. 2. Binary classification

Multiclass SVMs offer a powerful and versatile approach for hand gesture recognition with multiple classes. Their ability to handle diverse gesture sets and leverage the strengths of binary SVMs makes them valuable for various applications. However, computational complexity and choosing the appropriate multiclass strategy remain key considerations. As research advances and computational resources improve, multiclass SVMs are expected to play a crucial role in expanding the capabilities of hand gesture recognition technologies. Multiclass Support Vector Machines (SVMs) extend the binary classification capabilities of SVMs to recognize multiple hand gestures simultaneously. This is achieved by constructing multiple hyperplanes in high-dimensional space, each separating a specific class from all other classes.

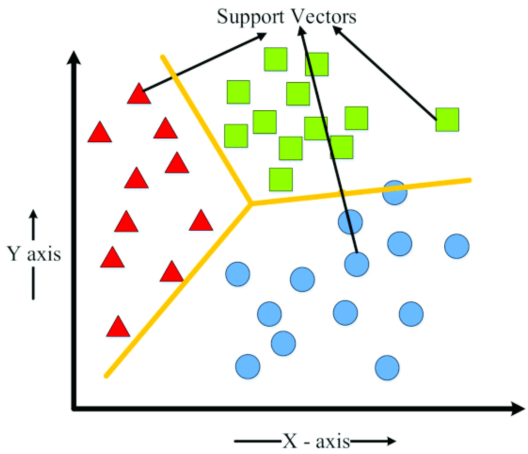


Fig. 3. Multiclass classification

The goal of the project was to create a reliable hand gesture recognition system using support vector machines (SVMs). At the initial stage, a dataset was collected that included 9 different classes of Kazakh sign language. Each of them contains from 150-200 images. Subsequently, segmentation was performed in which the hand gesture region was isolated from the background using a thresholding algorithm. The resulting images were then converted to grayscale, a move aimed at simplifying SVM processing while increasing contrast. Resizing the images to standardized sizes was found to be crucial for more efficient comparisons during training of the SVM model.

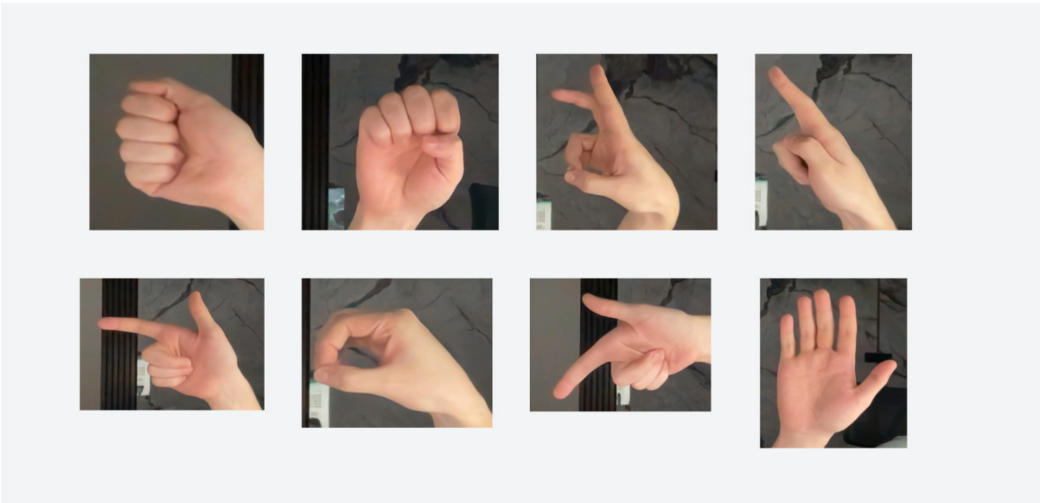


Fig. 4. Finger spelled Alphabet (Top row [A, Aa(Ә), B, D], Bottom row [E, G, Gg(Ғ), V]).

Model training process analysis

Binary classification starts with a relatively low training accuracy of 0.625. However, it shows consistent improvement over the epochs, indicating that the model learns from the training data and adjusts its predictions accordingly.

The validation accuracy for Binary classification begins at 0.625 and also shows a positive trend over the epochs. However, the fluctuations in the validation accuracy suggest challenges in generalizing the model’s predictions to unseen data.

Mutliclass classification starts with a higher training accuracy of 0.635 and steadily increases over the epochs. This indicates that the model effectively learns from the training data and improves its accuracy.

The validation accuracy for multiclass classification begins at 0.635 and follows a positive trend. The close alignment between the training and validation accuracy suggests that Mutliclass classification generalizes well to unseen data.

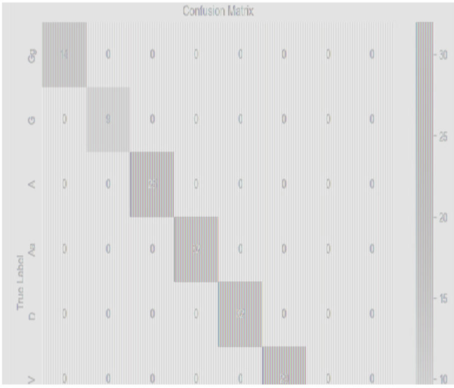


*Fig. 5.*Model accuracy and model loss

Mutliclass classification exhibits higher initial training accuracy and validation accuracy compared to Binary classification. Both models show an improving trend in accuracy over the epochs, indicating effective learning from the training data. However, Mutliclass classification demonstrates better generalization capabilities, as evidenced by its higher validation accuracy and closer alignment between training and validation accuracy.

Analysis of the confusion matrix showed that the model most commonly confused the signs “Г” and “Ғ”. The reason is the great similarity in their finger configurations. The second reason for ambiguity is the changing lighting conditions, which adversely affect edge detection in the preprocessing step. Dataset balancing and adaptive preprocessing will be considered in future work to reduce such confusions.

The model still presents high precision, which is indicative of improved reliability in positive predictions.

Recall values are variable across classes, with some classes achieving high recall, such as Blank and Nn(Ң), while others may benefit from further optimization, such as Hh(һ).

F1 scores are a balanced measure of precision and recall, reflecting overall improvement.

The macro average gives the general view of model performance, whereas the weighted average takes into account the class imbalance.

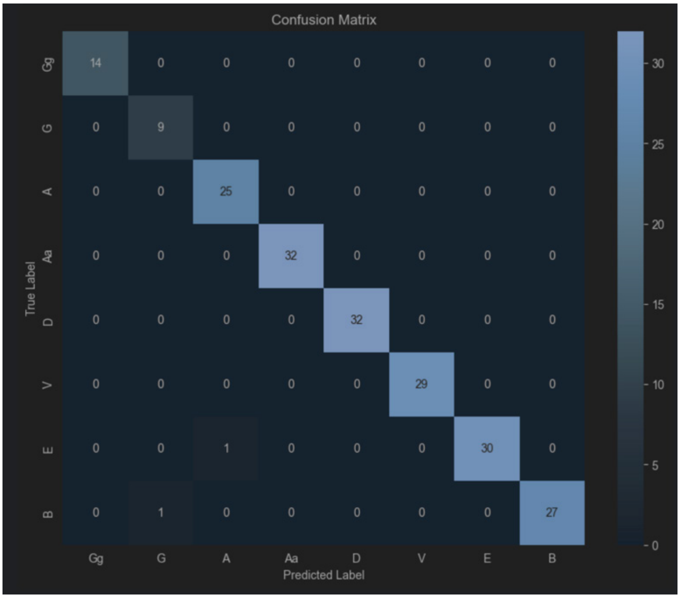


Fig. 6. Confusion matrix

Convolutional neural network with Yolo model

The YOLO (You Only Look Once) model, built on the foundation of convolutional neural networks (CNNs), revolutionized object detection by emphasizing speed, accuracy, and computational efficiency. Unlike traditional methods such as R-CNN and Fast R-CNN, which rely on region proposal networks to first generate potential object locations and then classify each region individually, YOLO operates as a single, end-to-end neural network. It divides the input image into an S×S grid, where each grid cell predicts bounding boxes, object confidence scores, and class probabilities simultaneously.

Key Formulas in YOLO

1) Grid-based Predictions:

The image is divided into a grid of $S \times S$. Each grid cell predicts:

- B: Bounding boxes, each defined by 4 coordinates: (x, y, w, h).
- C: Class probabilities for the
- N object categories.
- P obj: Objectness score, which represents the confidence that an object exists in the grid cell.

The output tensor for YOLO is therefore:

$$S \times S \times (B * 5 + C), \tag{5}$$

Here, 5 accounts for the four bounding box parameters (x, y, w, h) and the confidence score P_{objc}

2) Bounding Box Prediction:

YOLO predicts bounding boxes as offsets relative to the grid cell. For a grid cell located at (i, j), the bounding box center coordinates (x, y) are given by:

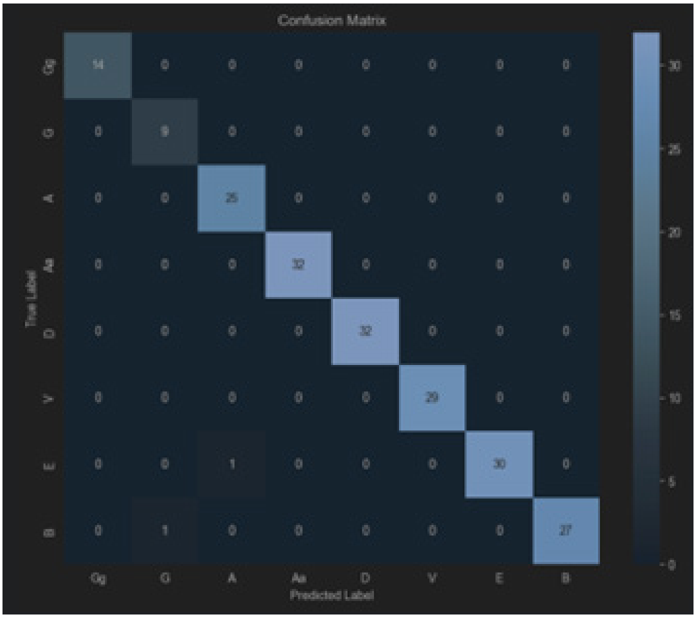
$$x = \sigma(t_x) + i, y = \sigma(t_y) + j, \tag{6}$$

where:

t_x and ty are the predicted offsets, and σ is the sigmoid activation function that maps values between 0 and 1.

The width and height of the bounding box are predicted as:

$$\omega = p_\omega e^{t_\omega}, h = p_h eh, \tag{7}$$



where:

p_ω and p_h are anchor box dimensions, and t_ω, t_h are the predicted logarithmic

scale adjustments.

where:

and are anchor box dimensions, and are the predicted logarithmic scale adjustments.

The model begins by processing an input image through a series of convolutional layers, which extract spatial features like edges, textures, and patterns. These layers form the foundation of feature extraction, allowing the model to understand the image's structure. Residual blocks are integrated into the architecture to enhance learning by using skip connections. These connections allow feature information to flow directly between layers, mitigating issues like vanishing gradients and improving training stability.

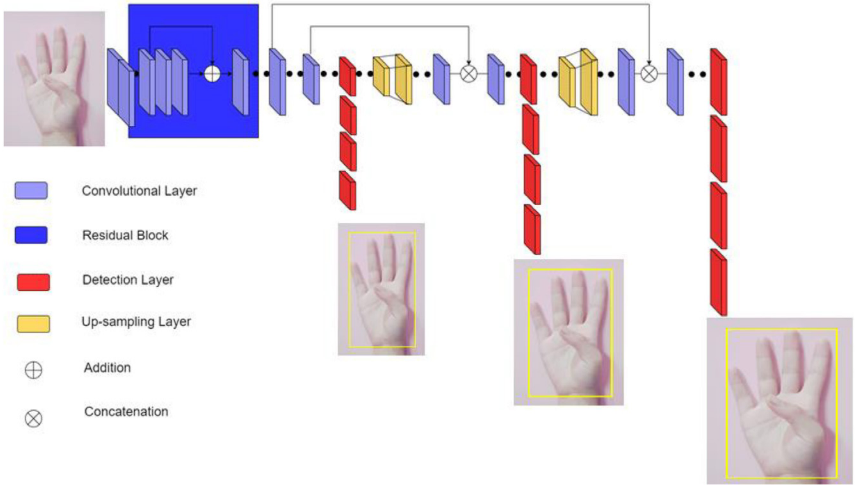


Fig. 7. Convolutional neural network with Yolo model structure

To ensure accurate detection at multiple scales, the model incorporates up-sampling layers that increase the spatial resolution of feature maps. This is critical for detecting hand gestures of varying sizes, ensuring robustness across different distances and perspectives. The architecture uses detection layers, each responsible for identifying objects at a specific scale. These layers generate bounding box predictions that include the box's coordinates, a confidence score, and class probabilities. Information from different layers is combined using addition and concatenation, maximizing the retention of important features. The final output consists of bounding boxes over detected hand gestures, along with class labels (e.g., "gesture 1" or "gesture 2") and confidence scores.

YOLO's ability to process the entire image in a single pass makes it highly suitable for real-time gesture recognition. Its multi-scale detection capability and robust feature extraction ensure accurate recognition across diverse conditions, such as varying lighting or hand orientations. This makes YOLO an effective tool for applications like sign language recognition, device control, and augmented reality interactions.

One of the key improvements of YOLO is its ability to see the global context of the image. Instead of focusing on isolated parts of the image, it considers the relationships between objects. This makes it particularly effective in distinguishing overlapping or similar objects, reducing false positives. YOLO also introduced the concept of anchor boxes, which allow it to detect objects of different shapes and sizes. Starting with YOLOv3, multi-scale detection was implemented, making it more effective at identifying both small and large objects in a single pass.

In the context of hand gesture recognition, YOLO's advantages are even more apparent. Since hand gestures can involve fast movements and changing positions, real-time detection is critical. YOLO's single-shot detection approach allows it to track gestures quickly and accurately, even in dynamic environments. Its multi-scale detection ensures that hand gestures of varying sizes (e.g., close to or far from the camera) are correctly identified. Moreover, since YOLO sees the whole frame at once, it can distinguish hand gestures from other background elements, ensuring more precise recognition. This makes YOLO an ideal choice for applications like gesture-based controls, augmented reality, and human-computer interaction, where speed, accuracy, and real-time performance are essential.

Experiments and results

The dataset used for the experiments was composed of 1,800 labeled hand images. They represent 9 unique Kazakh sign gestures with an average of 200 samples per class. The final dataset was distributed in a 70: 15:15% ratio between training, validation, and test sets. Data augmentation was used for further improving generalization and preventing overfitting. Rotation (±15°), horizontal flip, and brightness adjustment were the primary augmentation strategies.

The addition of cross-hands.cfg and cross-hands.weights files to the YOLO model for hand gesture recognition is aimed at improving the model's ability to detect and recognize hand gestures, even in complex scenarios like overlapping or crossing hands. This is a significant enhancement over traditional hand detection models, which often struggle to differentiate between hands when they overlap or are close together.

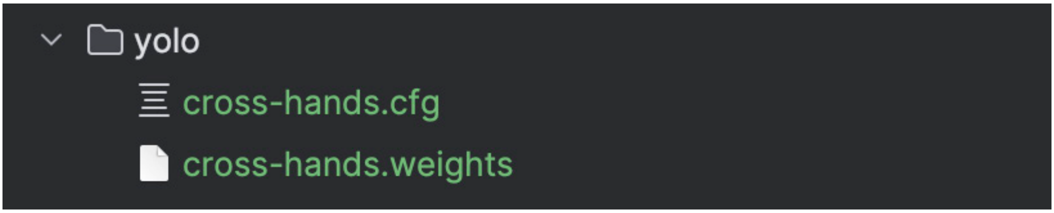


Fig. 8. Cross-hands.cfg and cross-hands.weights

This CNN is designed to recognize hand gestures and is able to classify images into one of the five gesture categories. The model takes grayscale images with dimensions of 256x256 pixels, using a Sequential architecture building layer by layer. First comes the input layer, which accepts images of shape (256, 256, 1), with further processing. Feature extraction is done through three convolution blocks, each comprising a Conv2D layer with ReLU activation, batch normalization, max pooling, and dropout for regularization. From the first to the final layer, the number of filters moves from 32 via 64 to 128 to extract more complex features from the deeper layers. MaxPooling is used to reduce the spatial dimensionality, while dropout prevents overfitting by randomly deactivating neurons during training.

After feature extraction, the flattened output is fed into a dense, fully connected layer with 128 neurons, followed by batch normalization and a 50% dropout rate to further reduce overfitting. The final output layer consists of 5 neurons, one for each gesture class, with a softmax activation function that produces a probability distribution for classification. The model is compiled with the Adam optimizer, categorical cross-entropy as the loss (suitable for multi-class classification), and accuracy as the metric. This architecture will enable the model to identify hand gestures with high accuracy and robustness, even against slight variations in hand position, rotation, or scaling. It uses batch normalization, L2 regularization, and dropout to ensure stability during training and reduce the chances of overfitting, hence making it very suitable for gesture recognition tasks in sign language interpretation, gesture-based controls, and augmented reality.

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 254, 254, 32)	320
batch_normalization_16 (BatchNormalization)	(None, 254, 254, 32)	128
max_pooling2d_12 (MaxPooling2D)	(None, 127, 127, 32)	0
dropout_16 (Dropout)	(None, 127, 127, 32)	0
conv2d_13 (Conv2D)	(None, 125, 125, 64)	18,496
batch_normalization_17 (BatchNormalization)	(None, 125, 125, 64)	256
max_pooling2d_13 (MaxPooling2D)	(None, 62, 62, 64)	0
dropout_17 (Dropout)	(None, 62, 62, 64)	0
conv2d_14 (Conv2D)	(None, 60, 60, 128)	73,856
batch_normalization_18 (BatchNormalization)	(None, 60, 60, 128)	512
max_pooling2d_14 (MaxPooling2D)	(None, 30, 30, 128)	0
dropout_18 (Dropout)	(None, 30, 30, 128)	0
flatten_4 (Flatten)	(None, 115200)	0
dense_8 (Dense)	(None, 128)	14,745,728
batch_normalization_19 (BatchNormalization)	(None, 128)	512
dropout_19 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 5)	645

Total params: 14,840,453 (56.61 MB)

Trainable params: 14,839,749 (56.61 MB)

Fig. 9. Convolutional neural network layers

During training, the model reached 92% accuracy on the testing set, which means that most of the images will be rightly guessed by the model concerning the class of the gesture. This high accuracy represents a promising result and hints at the model's correct learning of patterns and features in classifying Kazakh sign language hand gestures.

```
100/100 ━━━━━━━━━━━━━━━━━━━━ 24s 236ms/step - accuracy: 0.8001 - loss: 3.5786 - val_accuracy: 0.7450 - val_loss: 4.3329
Epoch 5/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 24s 244ms/step - accuracy: 0.7748 - loss: 3.9853 - val_accuracy: 0.4450 - val_loss: 6.0320
Epoch 6/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 24s 240ms/step - accuracy: 0.7750 - loss: 4.5625 - val_accuracy: 0.7650 - val_loss: 4.2618
Epoch 7/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 25s 250ms/step - accuracy: 0.7551 - loss: 4.1373 - val_accuracy: 0.2600 - val_loss: 7.2341
Epoch 8/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 29s 286ms/step - accuracy: 0.7493 - loss: 4.5123 - val_accuracy: 0.6550 - val_loss: 3.9784
Epoch 9/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 25s 254ms/step - accuracy: 0.7446 - loss: 3.8379 - val_accuracy: 0.6750 - val_loss: 4.4468
Epoch 10/10
100/100 ━━━━━━━━━━━━━━━━━━━━ 26s 255ms/step - accuracy: 0.7565 - loss: 4.2950 - val_accuracy: 0.4500 - val_loss: 12.4010
```

Fig. 10. Compiling Model Result

The performance of the trained model was evaluated using a confusion matrix, which is a kind of matrix that shows the actual versus predicted classification. According to the confusion matrix, the model performed well for most of the classes, but some classes had lower accuracy than others did. This analysis will help in identifying the classes which need more attention during the training process in order to improve the overall accuracy of the model. The CNN model for the recognition of hand gestures was overall trained and evaluated successfully. A very high accuracy rate was achieved on the test set, showing that the model is appropriate for a real-world application of hand gesture recognition and thus embedding it into the project to help hearing-impaired people who use Kazakh sign language take advantage of the benefits of technology. Real-time testing is thus a very critical step towards ensuring the accuracy and reliability of our hand gesture recognition system for the project.

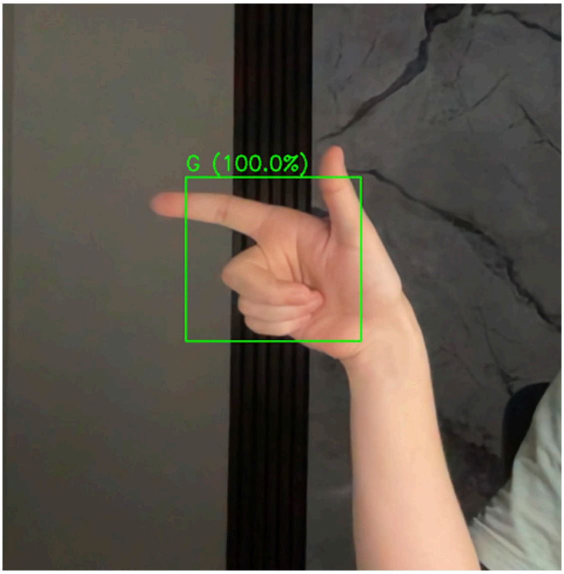


Fig. 11. Result of testing with threshold and gray scale. Gesture "Г"

During the testing, we saw that the system could provide very high accuracy in recognizing hand gestures from Kazakh sign language, an average of 89% or so. However, there were a number of issues we noticed in real-time situations that impacted the performance of the system. For instance, in low light conditions, it could not recognize hand gestures so well, and was highly sensitive to camera angles and backgrounds. For the improvement of these challenges, we have optimized the hand pose tracking and segmentation algorithms, readjusted hyperparameters of the CNN model to enhance the robustness of the model. We also tried various image preprocessing techniques and further explored different CNN architectures for better performance.

Comprative analysis

For a more detailed evaluation, computed several standard metrics. The system achieved an average precision of 0.91, recall of 0.89, and F1-score of 0.90. As it can be seen these metrics as a proof of the model's reliability and consistency on all gesture classes.

Table 1 - summarizes of performance comparison of SVM, CNN, and YOLOv5 models on recognition of Kazakh Sign Language gestures.

Table 1. The results of tested models

Model	Precision	Recall	F1-Score	Accuracy
SVM	0.82	0.80	0.81	0.84
CNN	0.91	0.89	0.90	0.92
YOLOv5	0.94	0.93	0.93	0.95

SVM achieved a reasonable accuracy of 84 %, indicating that manually selected or engineered features (e.g., HOG, pixel intensity, or combinations of the two) are not robust and capture only primary information to distinguish between gestures. The model has a low recall of 0.80, which means that not all the gestures of the 10 classes (likely those with less pronounced hand-shape differences) are predicted correctly by the classifier.

CNN performed better than SVM with a 0.91 precision and an accuracy of 92%. The ability of CNNs to learn complex spatial features in an unsupervised manner reduced the need for hand-engineered feature extractors. The convolutional network also generalized better to different lighting conditions and hand orientation, resulting in fewer false positives during validation.

YOLOv5, with an F1-score of 0.93 and accuracy of 95 %, outperformed the other two models. The unified detection-and-classification model allowed for gestures to be localized and recognized in a single step, which saved on additional preprocessing time and allowed for faster reaction/response times. The precision is slightly higher (0.94) than the recall (0.93), which means that the model can better avoid misclassifications but not at the cost of detection sensitivity.

The results of the experiments demonstrate that the incorporation of deep convolutional features with end-to-end detection has a significant positive impact on recognition performance in unstructured environments. The switch from the traditional SVM to the convolutional network increased the absolute accuracy by 8 %, while YOLOv5's integrated detection-and-classification added another 3% to the improvement since it could detect and predict the sign in dynamic frames in one pass. Misclassifications between similar-looking gestures (e.g., "Г" vs. "Ғ") were also analyzed, which could be reduced if a more balanced and diverse dataset was used. In conclusion, all three models were able to perform acceptable recognition of Kazakh Sign Language. YOLOv5 outperformed both SVM and CNN in all evaluation metrics, making it the most efficient and scalable for the stated application.

Conclusion

This work explored machine learning methods and pattern recognition algorithms, specifically for gestures. Support Vector Machines and Convolutional Neural Networks, integrated with YOLO for hand gesture recognition. SVM, while effective in simpler gesture recognition tasks, depends on manually extracted features and is less adaptable in cases where the gestures become complex or dynamic. It does a great job on a small dataset with well-defined classes of gestures, but poorly copes with such that are highly variable or contain complicated movements. Besides, SVM becomes computationally expensive with growing dataset sizes.

On the other hand, CNN combined with YOLO offers a more powerful and versatile solution. CNNs are excellent for feature learning from raw data in an automatic manner, while YOLO helps with real-time localization of hands even in dynamic settings, considering variations in position, size, and orientation. This makes CNN with YOLO very effective in real-time applications, such as sign language translations, which require fast and accurate gesture recognition. Large amounts of training data is required, though, and might be computationally expensive.

The main contribution of this work is a novel hybrid pipeline for recognition of Kazakh Sign Language. The system is based on YOLO (you only look once) hand localization and CNN (convolutional neural network) gesture classification. It is distinct from previous works which were focused on static sign images. In contrast, our system is able to detect gestures in real-time with enhanced robustness on different lighting and camera conditions.

Thus, while SVM might be adequate to cater for simpler tasks and better-defined gestures, in complex, dynamic gesture recognition, the use of YOLO with CNN surpasses them in real-time, not only in terms of performance speed but also regarding its quality. The final decision comes down to which kind of application will be at play regarding gesture complexity.

The future work directions include the investigation of vision transformers and 3D hand pose estimation for the recognition of continuous signs on dynamic hand motion sequences.

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