Yapay Zekâya Dayalı Robot Kol ile Hareket ve Farklı Nesnelerin Sertlik Kontrolü

Araştırma Makalesi/Research Article

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Özet— Çalışmada 3D baskı teknolojilerinden Fused Deposition Modeling (FDM) yazıcı kullanılarak robotik kol üretilmiştir. Üretilen robot kolun görüntü işleme teknikleri ve makine öğrenme algoritmaları kullanarak dokunsal algılama ve hareket planlaması araştırılmıştır. Bu çalışmanın amacı, robotik kolun kontrolsüz kuvvet uygulamasını engellemek ve dokunsal kavrama sorunlarını çözmek için görüntü işleme teknikleri ve derin öğrenme algoritmaları kullanılarak yenilikçi yaklaşımların araştırılması ve uygulanmasıdır. Bu çalışmada, CAD programı ile tasarımı gerçekleştirilmiş parçaların FDM tipi üç boyutlu yazıcı kullanılarak katı modelleri alınmış ve montaj için uygun hale getirilmiştir. Montajı tamamlanan robotik elin kontrol sistemi ise temel olarak Raspberry Pi kontrol kartı, servo motorlar, basınç sesörleri ve kameradan oluşmaktadır. Robotik kola ait her parmak ucuna yerleştirilen basınç sensörleri ile ürünün sertliği ölçülerek dokunsal algılama işlemi gerçekleştirilmiştir. Raspberrry pi kontrol kartı kullanılarak sensörlerden alınan veriler işlenmekte ve servo motorlara uygun hareket ve kavrama basınç bilgisi gönderilmektedir. Kamera kullanılarak elde edilen insan elinin olası hareketleri ile robotik kol için referans bir veri seti hazırlanmıştır. Veri setine ait görüntüler üzerinde Gaussian filtreleme yöntemi kullanılarak görüntü işleme sağlanmıştır. Bununla birlikte veri seti üzerinde makine öğrenme algoritmaları kullanarak robotik kolun hareket açısal konumu optimize edilmiş ve HitNet, CNN, Kapsül Ağları ve Naive Bayes derin öğrenme modelleri kullanılarak robot kolun hareket planlanması %90 doğruluk oranı ile sınıflandırılmıştır. Performans değerlendirme kriterlerine göre başarıları kıyaslanan derin öğrenme modelleri arasında, robotik kolun hareket planlaması için; HitNET algoritması ile 97.23%, CNN ile 97.48%, Capsnet algoritması ile %98,58 ve Naive Bayes modeli ile %98.61 doğruluk oranı elde edilmiştir. Performans değerlendirme kriterleri sonucunda; Naive Bayes modelinin %98.61 doğruluk, %98.63 özgüllük, %98.65 duyarlılık, 1.39 hata oranı ve %68.64 F-ölçüsü değeri ile diğer modellere göre daha başarılı sonuç verdiği gözlemlenmiştir.

Anahtar Kelimeler— yapay zekâ, robotik sistemler, üç boyutlu baskı teknolojileri, hareket kontrolü

Motion Control of the Robot Arm Manufactured with a Three-Dimensional Printer and Hardness Detection of Objects

Abstract— In the study, a robotic arm was produced using a Fused Deposition Modeling (FDM) printer, one of the 3D printing technologies. Tactile sensing and motion planning of the produced robot arm was investigated by using image processing techniques and machine learning algorithms. This study aims to investigate and apply innovative approaches using image processing techniques and deep learning algorithms to prevent uncontrolled force application of the robotic arm and to solve tactile grip problems. In this study, solid models of the parts were designed by CAD program and manufactured using FDM type three-dimensional printer. The control system of the robotic hand consists of a Raspberry Pi control card, servo motors, pressure sensors, and a camera. Tactile sensing was performed by measuring the hardness of the product with pressure sensors placed on each fingertip of the robotic arm. Raspberry pi control card is receive the data from the sensors are process them, after that the appropriate motion and clutch pressure information is sent to the servo motors. A reference data set for the robotic arm was prepared with the possible movements of the human hand obtained using the camera. Image processing is provided by using the Gaussian filtering method on the images of the data set. In addition, the angular position of the robotic arm's motion was optimized using machine learning algorithms on the data set, and the motion planning of the robot arm was classified with 90% accuracy using HitNet, CNN, Capsule Networks, and Naive Bayes deep learning models. Among the deep learning models which were very successful are compared each other according to the performance evaluation criteria, for the motion planning of the robotic arm; The accuracy rate was 97.23% with the HitNET algorithm, 97.48% with CNN, 98.58% with the Capsnet algorithm and 98.61% with the Naive Bayes model. As a result of the performance evaluation criteria; It has been observed that the Naive Bayes model gives more successful results than other models with 98.61% accuracy, 98.63% specificity, 98.65% sensitivity, 1.39 error rate, and 68.64% F-measure value.

Keywords— artificial intelligence, robotic rystems, 3D printing technologies, motion control

1. INTRODUCTION

Today, with the developing technology, robotic systems are used primarily in industry, agriculture[1], medicine[2], education[3], logistics[4], etc. Robotic systems have the potential to perform defined tasks uninterruptedly with a minimum error rate within the framework of certain algorithms [5]. It is being studied on the perception of the environment, and objects in the environment and the development of motion-position capabilities of robotic systems supported by artificial intelligence. This development of robot technology provides great advantages in terms of accelerating production, increasing the quality of work and preventing dangerous situations that may occur. The development of an artificial hand with an artificial hand has been achieved [6]. This robotic system, called the bionic hand, can move with the degree of freedom that the human hand has, provide similar joint movements, to perceive and grasp objects, change the location of objects, and in short, manipulate objects. provides the opportunity [7,8]. The sensory receptors of the human hand, which are the inspiration for the bionic hand system, are the external heat, light, pressure, chemical substances, etc. It obtains information about the stimulus by detecting such stimuli and ensures that the necessary actions are taken. Based on these humanoid sensory receptors, the ability of bionic hands to recognize and grasp objects can be improved[9]. Various studies have been carried out to detect humanoid hand movements and control the robotic hand [10].

In the study, the designs of the robotic arm consist of a finger, palm, and arm parts. Then, the robotic arm, which was designed with a Fused Deposition Modeling (FDM) printer, which is one of the 3D printing technologies, was produced. The main control unit of the robotic arm consists of a Raspberry Pi card and servo motors, sensors, and a camera system. Electronic control of tactile sensing and motion planning was realized with a Raspberry Pi card. The robotic arm is likened to the human tendon structure with fishing line threads connected to servo motors and motion control is provided. Pressure sensors were used to measure the force applied by the fingers of the robot arm to the part, and experimental studies were conducted to create a data set with the value of the force on the part, servo angular position information, and a machine learning mechanism was developed. Human hand movements were taken with a digital video camera and the images were recorded to prepare the data set. Images were processed using the Gaussian filtering method. The mobility of the robot arm on the image data set obtained by the experimental study was trained using Hitnet, Capsnet, and CNN deep learning algorithms. Considering the results obtained from the three deep learning algorithms, the CapsNET algorithm was the most successful classifier, classifying robotic arm motion planning with an accuracy rate of 98.58%.

When the recent academic literature is reviewed, the study reveals an innovative method.

- The study includes the control of bionic hands using image processing techniques. In this way, limb movements can be imitated without the need for any control system.
- In the study, hand movement images were processed with different models, and the success of the models was revealed.
- The success of the models used in the classification of hand images is satisfactory.
- With the proposed method, sensitive grip problems in bionic hands can be eliminated.

2. LITERATURE REVIEW

Reviewing the studies related to the bionic hand that published in recent years, bionic hand control has been carried out with many different methods.

Sree et al. In their study carried out a bionic hand simulation using data from 8 sensors collected through MyoWare Muscle Sensor. They developed an approach based on electrical signals generated in the human musculature. The control of the bionic hand is provided by using machine learning and deep learning methods. For the classification of the data received from the sensors, K-Nearest Neighbor Algorithm (KNN), Support Vector Machine (SVM), and a machine learning algorithm created by mixing KNN and SVM were preferred. All algorithms were tested and the hybrid of SVM and KNN, which gave the highest accuracy was used. A 96.33% correct classification success was achieved in the study [11].

Hekmatmanesh et al. performed a bionic hand control using brain Electroencephalograph (EEG) signals. They used an algorithm called Lyapunov exponent (LLE) to solve the complexity of brain signals. The algorithm has been optimized to achieve high accuracy and precision in the traditional LLE algorithm. Water Drop (WD) and Chaotic Tug of War (CTW) optimizers are used for optimization. Next, the LLE algorithm identifies movement patterns from brain signals. The defined movements were classified by the SMSVM-GRBF algorithm. An accuracy of 72.31% was obtained in the study [12].

Ryew and Choi created a joint design with 2 degrees of freedom to perform finger movements in 3D. It has been observed in the study that bionic finger movements are very similar to human finger movements with the design made [13].

Hafiane et al. used computer vision techniques to detect hand movements and used the SURF feature extraction technique to determine the movements by making a 3D model of the hand imitating the movement defined by remote manipulation to perform a task[14].

Gomez et al developed an adaptive learning mechanism that allows a tendon-driven robotic hand to explore its motion possibilities, interact with objects of different shapes, sizes, and materials, and learn how to grasp and manipulate them [15]. H.Kawasaki et al. developed a robotic hand equipped with a force-sensitive resistor array, driven by servo motors placed on the entire joint, finger, and palm, called the Gifu hand II, which has four fingers with one thumb [16].

In Table 1, motion control, artificial intelligence methods used and the results obtained from artificial intelligence methods are shown in detail in the articles examined in the literature study.

Table 1. Literature review comparison

Authors of the study	Motion Control	The method used in the study	Classification	Result
Sree vd.,	MyoWare Muscle Sensor	Machine learning Deep learning	K-Nearest Neighbor Algorithm (KNN) Support Vector Machine (SVM)	%96.33
Hekmatmanesh vd.,	Electroencephalograph (EEG) signals	Largest Lyapunov Exponent (LLE)	SMSSVM-GRBF algorithm	%72.31
Gomez vd.,	Tendon-guided drive - sensor	The proposed neural network	Evolved neurocontroller	Object manipulation and object grasping
Hafiane vd.,	Telerobotic system- SURF features	Nearest neighbor approach RANSAC approach	-	%67 repeatability - motion recognition and robot motion control
Ryew and Choi	Magnetic Coupling	Double Active Universal Joint (DAUJ)	-	very close motion characteristics with the human.
Kawasaki vd.,	Servo Motor – six-axis force sensor – tactile sensor	Gifu Hand ‖	-	very close motion characteristics with the human
In this study	Raspberry Pi-Pressure Sensor	Gaussian Filter Deep Learning Algorithm	HitNet CNN **CapsNet**	97.23% 97.48% **98.61%**

3. MATERIAL AND METHOD

3.1. Material

3.1.1. 3d Printer Features

In this study, a 3D desktop printer was used to print the parts. First of all, the model designed with the CAD program was transferred to the 3D printer in .stl format via a portable memory and the printing process was started. Printer specifications are given in Table 2 below.

Table 2. 3D printer specifications used

Technical Sepcification	
Modeling Technology	*FDM*
Print Size	*250x250x400 mm*
Resolution	*SD Card*
File Formats	*+/-0.1 mm*
Printing Material	*PLA/TPU/wooden/carbon fiber etc.*

3.1.2 Convolutional Neural Network

Convolutional Neural Network (CNN), which is a multi-layered feed-forward artificial neural network, is one of the most frequently used methods in image processing [17]. CNN, which has an important place in the field of deep learning, also shows success in various applications such as face recognition[18], object classification [19], speech detection[20], and sign language recognition[21,22]. The most preferred CNN for dealing with computer vision problems is architecturally formed by adding convolution, pooling (sampling), and fully connected layers to the basic layers [23,24]. The layer structure of the CNN architecture is given in Figure 1 [25].

Feature extraction from the image is performed in the convolution layer. In the pooling layer, the computational load of the system is reduced by reducing the size of the feature maps and secondary feature extraction is performed [26,27]. The last layer, the fully connected layer, performs the classification process [17].

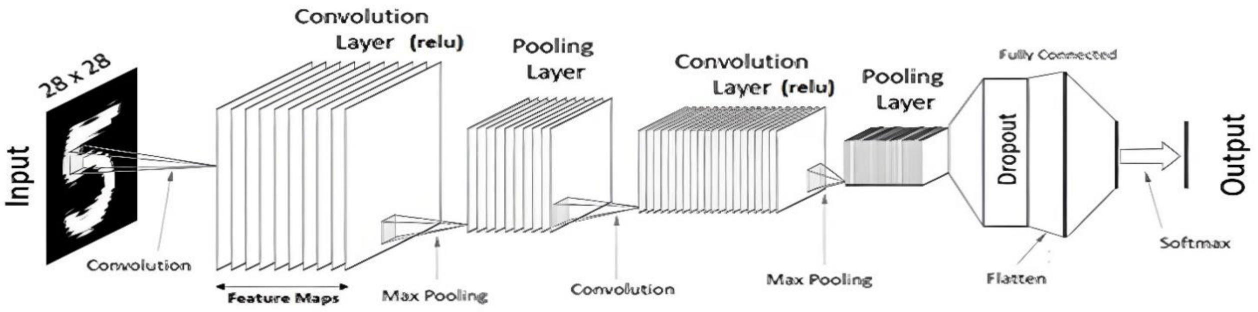

Figure 1. The layer structure of CNN architecture [31]

3.1.3 Hitnet

The HitNet architecture offers a new layer called the Hit-or-Miss layer, which can be used in different networks. The Hit-or-Miss layer contains active vectors called capsules, which are trained to hit or miss a central capsule by adapting a certain centripetal loss function. HitNet uses a ghost capsule system that enables the synthesis of image samples belonging to a particular class, detecting mislabeled images in training data by incorporating a new configuration network into the architecture[28]. The layer structure of the HitNET architecture is given in Figure 2.

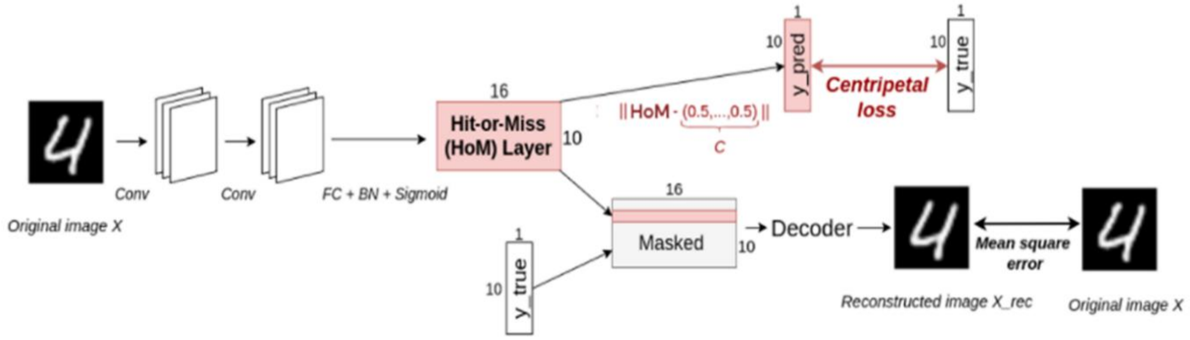

Figure 2. Graphical representation of hitnet architecture [29]

The new Hit-or-Miss layer consists of a centripetal loss, prototypes that can be built with a decoder, and ghost capsules that can be embedded in the HoM layer.

3.1.4 Capsule Network

Capsule Networks (CapsNet), Sabour et al. (2017) is a new image classification method introduced to avoid limitations and deficiencies such as not being able to reveal the relationship between the location of the object and the part, which occur in CNN algorithm applications [30,31]. A capsule is defined as a group of neurons in the CapsNet architecture. The input to a premise capsule is the output or features from a CNN algorithm. To obtain vectors from the outputs, resizing is done [32]. The CapsNet architecture consists of many layers, similar to the neural network model. Each of the low-level pods, also known as primary pods, is called a receiver and takes as input a specific region of the image in terms of position, stance, and part-relationship. Orientation capsules in higher layers detect larger and more complex objects (Figure 3) [33,34].

While the output values obtained from CNN architectures give a scalar value, the output of the capsule networks gives a vector value. Therefore, it cannot use scalar input values such as Relu, Sigmoid, and Tangent as in CNN. In contrast, capsule networks use a vectorial activation function known as squashing given in equation 1 [35].

$$v_j = \frac{||s_j||^2}{1+||s_j||^2}\frac{s_j}{||s_j||} \quad (1)$$

In the equation, sj represents the capsule input and vj the output vector of the capsule. The output vector (vj) shrinks the long vectors towards 1 if there is an object in the image, while it suppresses the short vectors towards zero if there is no object in the image.

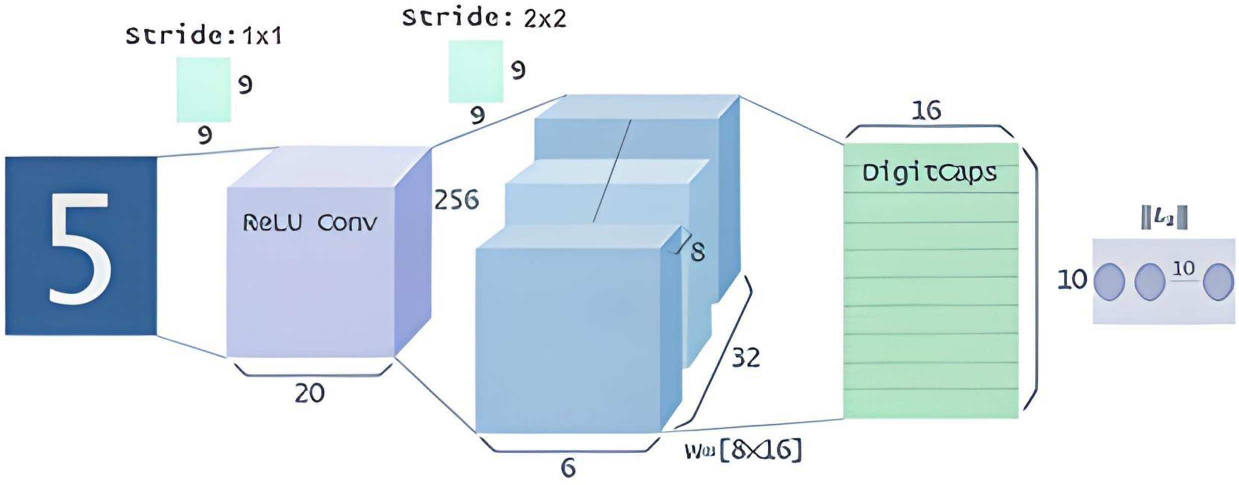

Figure 3. The layer structure of CapsNET architecture [34]

3.1.5 Gaussian Filtering

Image processing is a method that enables the definition of objects or people in the image and the desired interpretation by processing and improving digital image data with certain algorithms [36]. In the image processing method, firstly, image pre-processing steps are applied to the images taken from the camera, and various filtering processes are performed [37]. The Gaussian filtering technique used in the study is a 2D convolution filter used in image smoothing and noise removal on the image [38].

The probability Density Function (P(x)) of the Gaussian distribution is given in Equation 2.

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(x-\mu)^2/(2\sigma^2)} \quad (2)$$

In the equation, x is a gray level image, μ is the mean value, and σ is the standard deviation. Gauss' standard deviation (σ) determines the amount of smoothing[39].

3.1.6 Performance Evaluation Criteria

Various performance evaluation criteria are used to evaluate the findings and algorithm performances obtained as a result of classification [40]. The performance of the algorithms is obtained from the complexity matrix; It is evaluated based on evaluation criteria such as sensitivity, specificity, precision, accuracy, and F-measure criteria [41]. Classification criteria; It is determined as True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). The complexity matrix is shown in detail in Table 3 [42].

3.1.6.1 Sensitivity Criteria

Sensitivity is expressed as the ratio of the number of correctly classified samples (TP) to the sum of the number of true positive (TP) and false negative (FN) samples and is expressed as shown in equation 3 [43].

Table 3. Complexity matrix

		Predicted Class	
		Class X (Positive)	Class Y (Negative)
Real Class	Class X (Positive)	TP	FN
	Class Y (Negative)	FP	TN

$$\text{Sensitivity (recall)} = \frac{TP}{TP+FN} \quad (3)$$

3.1.6.2 Specificity Criteria

Specificity is expressed as the ratio of the number of correctly classified samples (TN) to the sum of negatively classified samples, and its mathematical expression is given in equation 4 [44].

$$\text{Specificity} = \frac{TN}{TN+FN} \quad (4)$$

3.1.6.3 Precision Criteria

The precision criterion shows how many of the positively predicted values are real positive and is expressed as shown in equation 5 [44].

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

3.1.6.4 Accuracy Criteria

The accuracy criteria give the success rate of a model. Accurate estimates are found by dividing all data. In Equation 6, the mathematical expression of the accuracy criterion is given. The error criterion, on the other hand, is determined by the ratio of the number of misclassified samples to the total number of samples, as seen in the complexity matrix, and is obtained by using the mathematical expression given in equation 7. The error rate is also found by subtracting the accuracy value from 1 [44,45].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$\text{Error Rate} = 1 - ACC \quad (7)$$

3.1.6.5 F-Score Criteria

The F-Score criteria gives the harmonic mean of the precision (Precision) and sensitivity (Recall) values. With the harmonic mean, extreme values are included in the evaluation and incorrect model selection is avoided in data sets that are not evenly distributed. F-score is given with mathematical expression in Equation 8 [46].

$$\text{F-Score} = \frac{2\times(precision \times recall)}{precision + recall} \quad (8)$$

3.2. Method

3.2.1 Design And Manufacturing of The Robotic Hand

In the study, firstly, the design of the necessary parts for the manufacture of the robotic hand was drawn in the CAD program. The resulting drawings were saved as .stl extension and made ready for three-dimensional printing

with an open-source slicing software. The parts created during the design phase are shown in Figure 4. Solid models of the parts passing through the design phase were taken using a three-dimensional printer and made suitable for assembly. The PLA material used for the design of robotic handpieces has been preferred in the study as it is light, economical and durable enough to make the robotic hand portable.

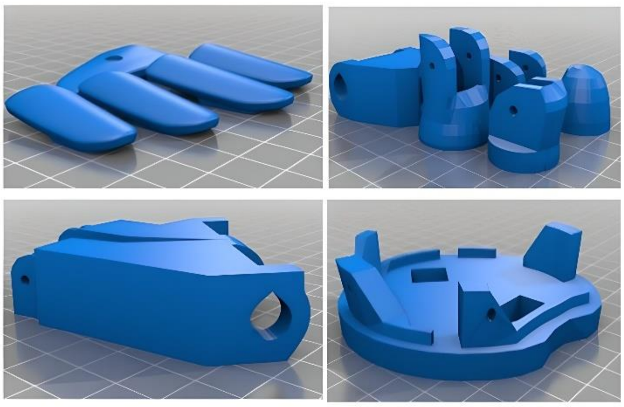

Figure 4. The parts created during the design phase

By bringing together the parts of which solid models were created, the finger limbs of the robotic hand were created as shown in Figure 5, and the robotic hand was formed by bringing the fingers together with the palm. MG995 Servo motors, and fishing line threads that act as tendons are used to provide movement transmission between the fingers.

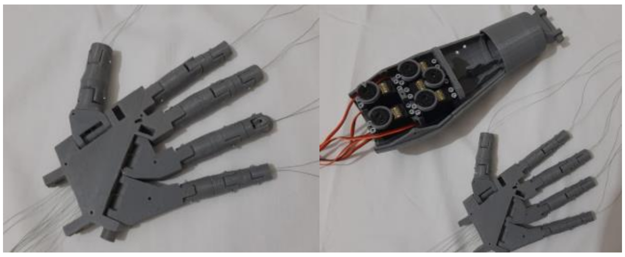

Figure 5. Finger limbs and robotic hand

3.2.2 Classification of Hand İmages and Pressure Sensor Data

After the design and manufacturing stages of the robotic hand were completed, two different data sets were created, hand images and pressure data, as shown in the workflow diagram given in figure 6. First, reference hand images were modeled on the computer. The hand images represent the movements that the robotic hand must make. By labeling the obtained images, the data set was made ready for training. The data set was trained by using CNN, CAPSNET, and HİTNET architectures from deep learning algorithms. 80% of the dataset is training and 20% is the test dataset. The deep learning architectures used were evaluated according to complex matrix and accuracy performance evaluation criteria. In the second stage, pressure data in three different categories were obtained. These categories were created according to the degree of hardness of the objects to be grasped by the robotic hand. By attaching three different hard objects, soft, medium and hard, to the robotic arm, data were collected instantaneously from the pressure sensors on the finger, and palm. The data obtained were labeled in three categories soft, medium, and hard. The collected data were subjected to missing data analysis, feature selection and scaling processes. The prepared data set is trained with a naive bayes machine learning algorithm. 80% of the dataset is training and 20% is the test dataset. The machine learning algorithm used was evaluated according to complex matrix and accuracy performance evaluation criteria.

All deep learning-based models used in the study were trained under the same conditions and with the same dataset. The training process was done in the open-source python programming language platform. Learning rate is one of the most important hyperparameters to be adjusted during training deep learning architectures. If the learning rate is set low, very small updates in the weight of the network architecture will occur, making the training progress very slowly and the probability of overfitting increasing. In addition, if the learning rate is set too high, the verification loss increases, and the accuracy of the architecture decreases. To find a solution to these two problems that may arise in the study, the learning rate hyperparameter for all models was determined using the cyclic learning rate method. In the cyclic learning rate method, minimum, maximum, and maximum limits are determined and the learning rate changes cyclically between these limits. This method provides improved classification accuracy, without any adjustments and generally with fewer iterations, using the cyclic learning rate instead of fixed values. The hyperparameter values of artificial intelligence models used in training are given in Table 4.

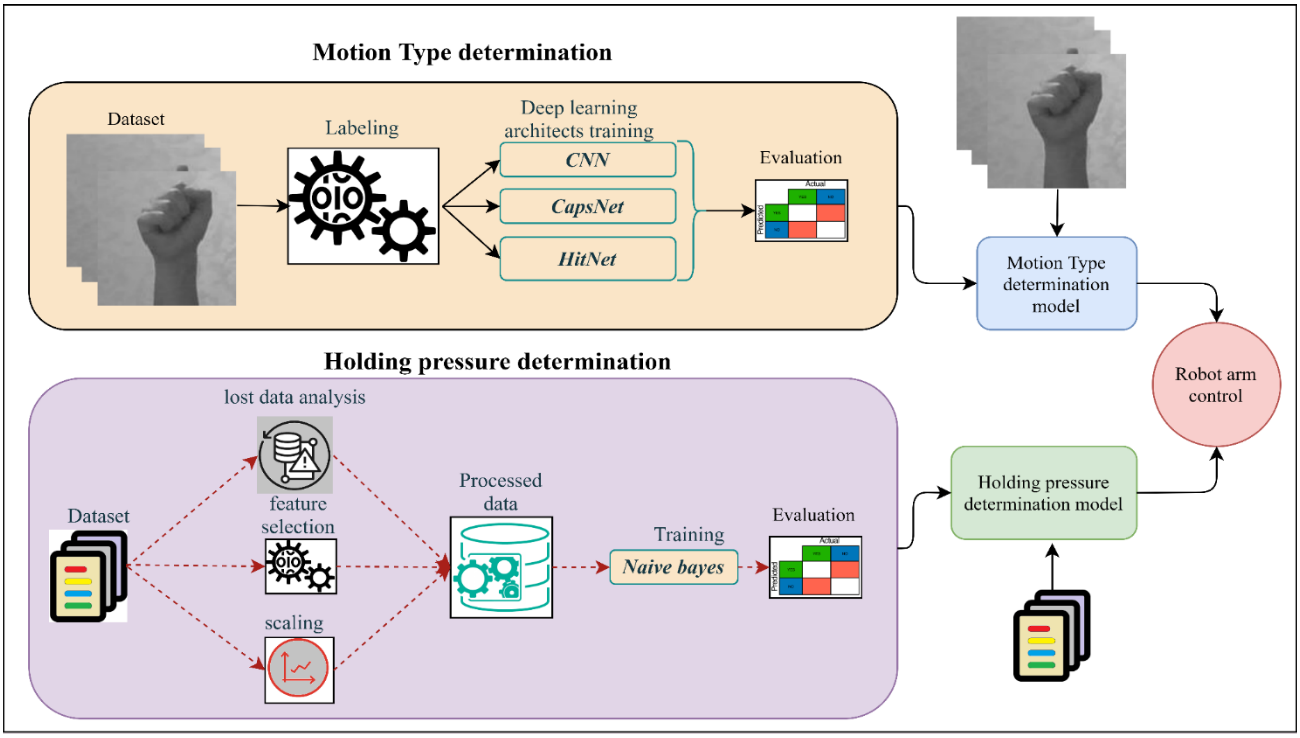

Figure 6. Workflow diagram of hand images and pressure data

When the table is examined, all deep learning models are trained with 24x224x3 image size and 50 epochs. The learning rate of the CNN model, which consists of 23 convolution layers in total, was determined as 0.001 using the cyclic learning rate method. Using the same optimization method, the learning rate for the CapsNet model was chosen as 0.005 and for HitNet as 0.001. In the study, the cyclical learning rate method was used to determine the optimal learning rate values of all models. The learning rates choose according to learning rate–loss graphs of all models. By using optimal learning rate values and tuning the other parameters we get high accuracy in all models.

Table 4. parameters values of the artificial intelligence models

Artificial Intelligence Models	Hyperparameters	Values
CNN	Number of convolution layers	23
	Learning rate	0.001
	Epochs	50
	Image size	224x224x3
CapsNet	Learning rate	0.005
	Epochs	50
	Image size	224x224x3
HitNet	Learning rate	0.001
	Epochs	50
	Image size	224x224x3

To examine whether there are problems such as overfitting in the deep learning models trained in this study, 20% of the training data was used for validation at the end of each epoch. Test datasets were used to test only the final version of the model. The final models showed very high success on the test datasets.

3.2.3 Robotic Hand Control System

The control system of the robotic hand consists of a Raspberry Pi control card, servo motors, pressure sensors, and a camera. Fingers are driven by MG995 servo motors for the movements to be performed with the robotic arm. Servo motors are located on the arm of the robot as seen in figure 7. The mobility of the robot arm is based on the tendon system in the human muscle structure.

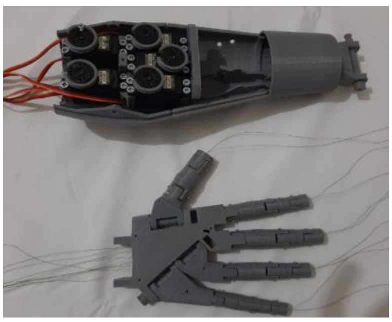

Figure 7. Servo motors located on the robotic

The movement of servo motors has been transferred to the fingers by using fishing line threads and mobility has been gained. The angular rotation data that will enable the movement of the servo motors are determined according to the estimation results obtained from the deep learning architectures running on the Raspberry Pi. In the study, 3 different deep learning architectures, CNN, HitNET, and CapsNET, were used in the Python 3 Idle interface, and hand motion images taken from the camera module were transferred to these architectures instantly.

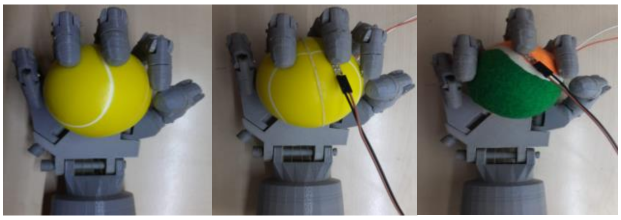

Figure 8. The use of pressure

At this stage, certain movement limitations are needed so that the robot arm can make a precise grip without damaging the objects. These limitations vary according to the compressive strength of the objects. As seen in Figure 8, the pressure response of objects of different hardness was measured with the RP-C7.6-ST thin film pressure sensor used in the finger and palm of the robotic hand, and a data set was created with these values. The created data set was classified by training on Raspberry Pi. While the robotic arm is grasping the objects, the data instantly received from the pressure sensor is processed in the trained machine algorithm and a result is produced. In line with the produced result, the compressive strength of the object grasped by the robotic hand is classified with 99.9% accuracy. According to the differences in compressive strength, the maximum angles of the motor movements are limited by the Raspberry PI card.

4. RESEARCH FINDINGS

In the study, hand images obtained with the camera were classified using CNN, HİTNET, and CAPSNET deep learning architectures, and the angular rotation data of 5 motors of the robot arm were determined. In addition, a naive bayes machine learning-based decision system has been developed to determine the pressure force limit that the motors of the robot arm will apply to the objects to be grasped.

1550 images were used as a test dataset in the evaluation of CNN architecture. There are 31 different classes in 1550 images in the test dataset. 1511 of the test data were predicted correctly with the CNN model, and 39 of them were predicted incorrectly and an accuracy rate of 97.48% was obtained (Figure 9).

1550 images were used as test dataset in the evaluation of HitNET architecture. There are 31 different classes in 1550 images in the test dataset. 1507 of the test data were predicted correctly with the HitNET model, 43 of them were predicted incorrectly and an accuracy rate of 97.23% was obtained (Figure 10).

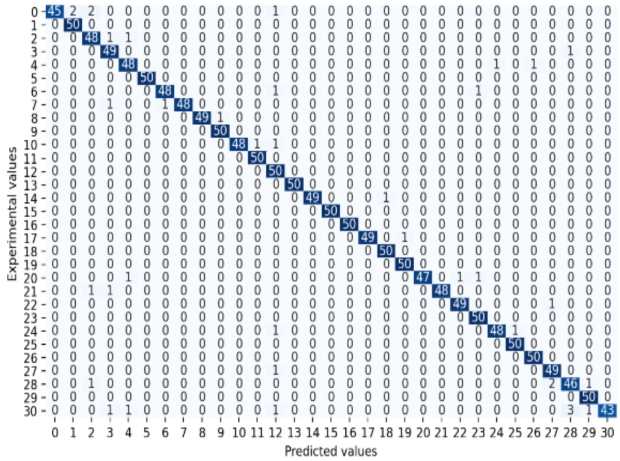

Figure 9. Confusion matrix of CNN architecture

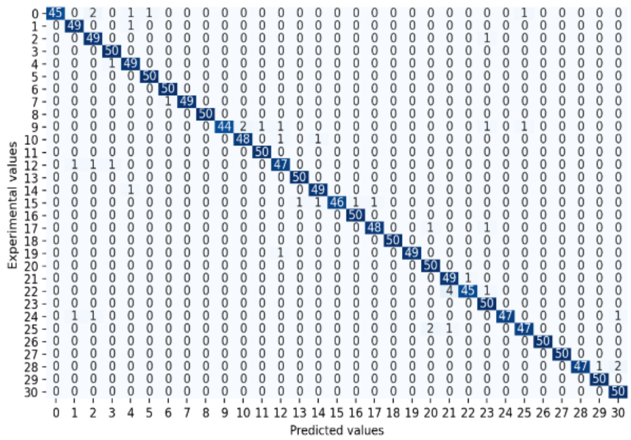

Figure 10. Confusion matrix of HitNET architecture

1550 images were used as test dataset in the evaluation of CapsNET architecture. There are 31 different classes in 1550 images in the test dataset. 1528 of the test data were predicted correctly with the CapsNET model, 22 of them were predicted incorrectly and an accuracy rate of 98.53% was obtained (Figure 11).

In the realization of the naive bayes machine learning-based decision system, a total of 2155 data, 1724 of which are training and 431 of which are test data, are divided into three categories soft, medium, and hard. 425 of the test data were predicted correctly, 6 of them were incorrectly estimated, and an accuracy rate of 98.61% was obtained (Figure 12).

The accuracy rates obtained with deep learning and machine learning architectures used for hand images and pressure data are given in Table 5.

In Table 6, the results obtained from the CNN, CapsNet, Hitnet and Naive Bayes deep learning models used in the study are given according to the performance evaluation criteria of Sensitivity, Precision, Accuracy, Error Rate and F-Score.

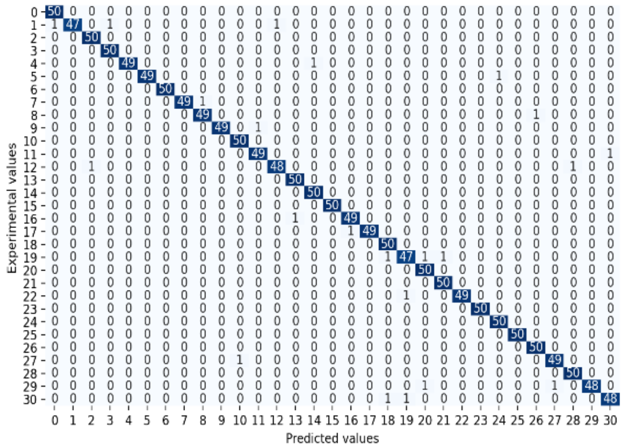

Figure 11. Confusion matrix of CapsNET architecture

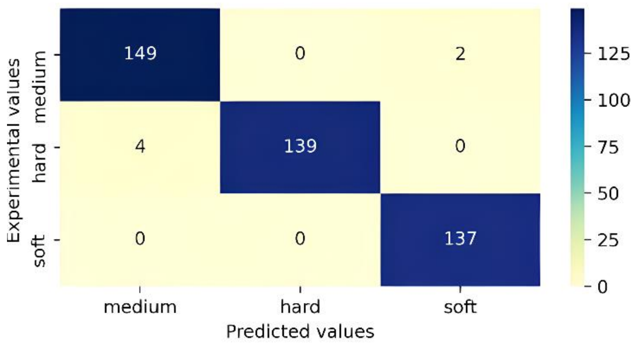

Figure 12. Confusion matrix of naive bayes

Table 5. Accuracy table of hand images and pressure data

Data Set	Artificial intelligence models	Accuracy
Hand images	CNN	97,48
	HitNet	97,23
	CapsNet	98,58
Pressure data	Naive Bayes	98,61

5. DISCUSSION

When the academic literature related to the study was examined, Tan et al. developed a multi-fingered robot hand using a hydraulic actuation system with fluid actuators. All components of a miniature hydraulic system are placed in the palm. All finger parts of the prototype are integrated into a single unit. The two parts, the finger, and palm are made of urethane mold, a very flexible material. Fourteen knuckles with 14 DOFs are powered by fluid actuators that bend when hydraulic pressure is applied by a miniature water pump. The hand is designed to be operated restricted to only five degrees of controlled movement. Controlled by a programmed microcontroller, the hand can be operated automatically or manually.

In automatic mode, objects are automatically grasped when hand force sensors detect contact with objects. Clutch force is controlled by changing the PWM duty cycle given by the microcontroller. The hand can apply a force grip to grasp a 700 g mass. The developed prosthetic hand has the appearance of a human hand with its shape, size, and skin texture. In addition to being portable, the prosthetic hand can perform human movements such as grasping, throwing and pointing. However, with an increase in the amount of pressure applied, the prosthetic hand can grasp 2.4 kg objects by generating more power [47]. Zhuang et al. In their study, they designed an underdeveloped bionic hand with five fingers working with a pneumatic system. The five fingers are driven by a group of rollers in parallel. Each roller uses a joint and each group of rollers moves a finger. The joint angles of the fingers are determined according to the shape and size of the object to be grasped. With the increase in gas pressure, the joint with the minimum load starts to close as much as the rotation angle and the other joints repeat the same process. The resistors decide the order of movement of the fingers. When the grasped object is grasped with the desired force, the joints will stop and the air supply will be cut off. The force to be applied is determined after static and kinematic calculations [48]. Hirano et al. presented a new approach on a robot hand developed for identifying and grasping an unknown object among multiple unidentified objects. In the system under consideration, image-based 3D reconstruction and separation of multiple objects and path planning techniques are introduced using new visual object recognition and graphic-based theory. The size, shape, and orientation of the unknown target object in a cluttered scene are determined and comprehended according to the estimation results [49]. Mahboubi et al. In their study proposed a cost-effective, durable, and compatible gripper with wide hardness variability compared to existing robotic hand systems, which can be used in industrial areas. The proposed system creates a force for the tendon mechanism that can control the position and degree of stiffness of the fingers. The mechanism consists of two rotational servo motors. One of the servo motors can be used with a linear compression spring to control the stiffness of the fingers. The other motor is used to change the positions of the fingers. Thus, the desired gripping force can be achieved [50]. Mitsui et al. developed a robot hand based on human hand dimensions. Three special gearboxes have been developed for this robotic hand, which was developed based on mechanical accents, to be used between the joints, between the fingers, and the thumb. These special transmissions enabled four clutch operations to be performed using only three actuators and a solenoid. While reducing the volume and weight of the robotic hand, the gearboxes maintain the necessary functions to perform the desired grips [51].

Ruehl et al. In their study, they carried out an experimental evaluation of the grasping abilities of the Schunk 5 Finger Grip Hand (SVH), a fully anthropomorphic robot hand, using various objects of different sizes. In the developed system, while all the drivers are integrated into the hand, the motor controllers are fully integrated into the wrist. Thus, by using a standard interface, the gripper hand can be easily connected to the robot arm. The robot hand has 20 joints. Most SVH joints are actuated by lead screw mechanisms that convert linear motion into rotary motion. The robot hand has 9 DOFs driven by servo motors that rotate gradually with control system commands [52]. Jiang et al. have realized the design and production of a robotic hand with a fiber optic sensor that can be manipulated in many ways. Although the primary target of the study was a five-fingered robotic hand, they presented the study as a three-fingered gripper. The robotic hand has three fingers that can perform pinching and grasping the target object. The skeletal structure of the robotic hand is made of a hard plastic material and covered with soft skin. To realize tactile sensing, the skeleton structure includes eight fiber optic strain sensors and six fiber optic strain sensors embedded in the skin. While the sensors in the skeletal structure ensure that the correct forces applied to the hand are detected, the sensors in the soft skin provide information about the location of the contact points. In the realized design, the positions of the fingers on the hand can be changed and the optimum position of compression and grip can be adjusted. The functionality of the robotic hand is provided by the tendon system. All tendons in the three fingers are integrated into the HS-5485HB, HiTEC servo motor, which enables three fingers to be controlled simultaneously [53].

6. CONCLUSION

In this study, tactile sensing and motion planning of the robotic arm produced with Fused Deposition Modeling (FDM) printer, one of the 3D printing technologies, were investigated by using image processing techniques and machine learning algorithms. The hand images obtained with the camera and pressure data obtained from pressure sensors were classified by deep learning and machine learning algorithms and evaluated with performance evaluation criteria, and successful results were obtained.

- Firstly, CNN 97.38%, HitNET 97.23%, and CapsNET 98.58% accuracy rates were obtained from deep learning architectures used for the classification of hand images. From this point of view, it has been seen that the most efficient classifier for 1550 hand images is the CapsNET architecture with an accuracy of 98.58%.
- Secondly, the naive bayes algorithm was used to classify a total of 2155 pressure data, 1724 training, and 431 test data obtained from the pressure sensor, and an accuracy rate of 98.61% was obtained.
- Deep learning models; The success rate was examined according to the performance evaluation criteria consisting of accuracy, specificity, sensitivity, error rate, and F-score. As a result of the evaluation, it was observed that the Naive Bayes model gave more successful results than other models with 98.61% accuracy, 98.63% specificity, 98.65% sensitivity, 1.39 error rate, and 68.64% F-measure value.

Table 6. Performance evaluation criteria

Deep Learning Model	Performance Evaluation Criteria				
	Sensitivity	Precision	Accuracy	Error Rate	F-Score
CNN	94.39	98.52	97.48	2.52	96.41
CapsNet	98.60	98.58	98.58	1.48	98.59
HitNet	94.57	97.23	97.23	2.77	95.88
Naive Bayes	98.65	98.63	98.61	1.39	68.64

In line with the results obtained in the study, the performance of the study can be improved by using different deep learning models in future studies. At the same time, by adding a temperature sensor and a distance sensor in addition to the pressure sensor used for the robot arm, the distance between the robot arm and the object to be grasped can be calculated, and accordingly, the accuracy of the grip angles of the fingers can be increased. With the heat sensor, the temperature of the object can be detected. Thus, depending on whether the material of construction of the robotic arm is suitable for the temperature of the object, it can be decided whether the robotic arm will grasp the object or not. In future studies, using artificial intelligence-based optimization algorithms for the robotic arm, trajectory planning can be created depending on the position of the objects. Thus, the robotic arm can reach the object most shortly, and perform the gripping operation, and can act as a hold-and-release between the start and endpoints.

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