AI-POWERED HEALTHCARE INNOVATIONS: REHABILITATION, EDUCATION, AND EARLY DIAGNOSIS

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FOREWORD

In the 21st century, healthcare has experienced a seismic shift, driven by rapid technological advancements and the rise of artificial intelligence (AI). No longer limited to diagnostics and medical imaging, AI is now infiltrating areas such as patient rehabilitation, chronic disease prevention, and personalized treatment planning. This transformation is revolutionizing the way we approach healthcare, opening doors to more efficient, engaging, and data-driven methodologies. This book presents a deep dive into three pioneering fields within this new paradigm: gamified physiotherapy, AI-powered predictive tools for disease risk assessment, and AI-driven educational interventions in special needs care.

The first study, which explores the development of *Therapinno*, an AI-powered gamified physiotherapy platform, exemplifies how artificial intelligence and gamification can enhance patient engagement and motivation. Physiotherapy, a domain historically centered on repetitive and sometimes tedious exercises, has long struggled with patient adherence. However, by integrating game mechanics such as real-time body movement tracking, interactive feedback, and scoring challenges, *Therapinno* transforms the physiotherapy process into an enjoyable, interactive experience. The platform uses AI to analyze patients' movements in real-time, ensuring precise execution of therapeutic exercises while making rehabilitation feel like a game. This is not only a breakthrough in the rehabilitation process but also a step forward in patient-centric care, as it provides a personalized, fun, and motivating approach to physical recovery.

The second focus of the book is the application of AI in predicting disease risk, specifically in diabetes. Diabetes, one of the most prevalent chronic conditions globally, places a tremendous burden on both individuals and healthcare systems. Early diagnosis and lifestyle adjustments are critical in preventing or managing the disease. This book presents the development of an AI-powered web application capable of predicting an individual's risk of developing diabetes based on routine laboratory test results and lifestyle habits. By employing sophisticated machine learning algorithms, this system can analyze large amounts of data, identifying risk factors and offering predictions with a level of accuracy that traditional methods struggle to match. The integration of this AI-based tool into everyday healthcare practices highlights the potential for preventive interventions, empowering individuals to manage their health before conditions worsen.

In the third study, the book delves into the use of AI in special education, specifically in the context of gamified learning for children with special needs. This study demonstrates how AI and image processing can enhance educational experiences for children by creating tailored, interactive environments that respond to the unique needs of each learner. By incorporating real-time feedback and personalized exercises, this approach not only improves learning outcomes but also provides an engaging, supportive framework for children who often struggle in traditional educational settings. This innovative use of AI in education marks an important development in the way we approach learning for children with disabilities, demonstrating the broader applicability of AI-driven solutions beyond healthcare and into realms of personal development and social inclusion.

As you investigate these studies, you will witness the convergence of AI, healthcare, and gamification, a union that represents the future of personalized healthcare and education. These innovations demonstrate how AI can be seamlessly integrated into interventions, creating more engaging, efficient, and tailored solutions. From gamified physiotherapy platforms to AI-driven educational tools, this book offers a comprehensive view of how AI is reshaping healthcare delivery, patient engagement, and educational outcomes.

This book invites healthcare professionals, technologists, educators, and policymakers to reimagine not just healthcare but also learning as dynamic, interactive experiences that place the individual at the center. The future is no longer about treating illnesses or learning challenges after they occur but about preventing them and optimizing development before they take hold. By combining artificial intelligence with innovation in healthcare and education, we can create a more proactive, patient- and learner-focused future.

THERAPINNO: AI-POWERED GAMIFIED PHYSIOTHERAPY FOR PERSONALIZED REHABILITATION AND EXERCISES

This instance study focuses on the development and application of Therapinno, an AI-powered gamified physiotherapy platform designed to enhance patient motivation and engagement through real-time body movement analysis. By incorporating game elements such as scoring, challenges, and interactive feedback, Therapinno transforms conventional rehabilitation exercises into an enjoyable and immersive experience. Using the MediaPipe framework, the application analyzes users' movements, ensuring precise execution of therapeutic exercises, which are personalized to meet individual needs. This innovative approach not only improves adherence to physiotherapy regimens but also demonstrates the potential of AI-driven solutions in advancing healthcare delivery.

INTRODUCTION

Screen addiction in children has become a significant concern, particularly considering the increasing prevalence of digital devices and the changing dynamics of parenting and education. Research indicates that parental screen addiction plays a crucial role in children's screen use behaviours. For instance, a study found that children whose parents exhibit smartphone addiction are more likely to develop similar addictive behaviours, with older children (e.g., grade 8) showing higher addiction levels compared to younger ones (e.g., grade 5) (Son et al., 2021). This suggests that the home environment, influenced by parental habits, can significantly impact children's screen time and potential addiction. Moreover, the relationship between screen time and physical health outcomes, such as obesity, has been documented. A study involving elementary school students revealed that increased screen time correlates with higher Body Mass Index (BMI) values, indicating a link between screen addiction and obesity. This relationship is exacerbated by the marketing of unhealthy food products during screen time, which can lead to increased caloric intake among children (Kocakoğlu et al., 2021). Furthermore, excessive screen time has been associated with mood changes and developmental delays, underscoring the multifaceted consequences of screen addiction on children's mental and physical health (Thakur et al., 2022). Parental mediation is critical in managing children's screen time. Despite recommendations from pediatric societies to limit screen use, adherence to these guidelines remains poor (John et al., 2021). Factors such as parenting stress, particularly during the COVID-19 pandemic, have led to increased screen time as parents struggle to maintain authority over their children's media consumption (Hidaayah et al., 2022). The pandemic has exacerbated this issue, as remote learning has increased children's screen exposure, often without adequate parental supervision (Tandon et al., 2021). This lack of supervision can lead to maladaptive behaviours, including screen addiction, which manifests in symptoms such as preoccupation with screens and withdrawal when not using them (Li et al., 2022; Paranjape et al., 2022).

Physical rehabilitation is a healthcare field aimed at helping individuals regain functional independence following accidents, injuries, surgeries, or chronic health conditions that result in mobility limitations. Traditional physiotherapy methods typically consist of repetitive exercises, which can sometimes be monotonous or fail to engage patients effectively. However, in recent years, the concept of gamification has emerged as an innovative approach in physiotherapy practices. Gamified physiotherapy aims to make movement more enjoyable by encouraging greater patient participation in treatment. In the modern world, health and well-being are largely dependent on individuals' health-related behaviours. Motivation plays a critical role in altering these behaviours, and intrinsically driven behaviour changes are sustainable. (Johnson et al., 2016b).

Gamification is the application of game features, particularly video game elements, to non-game contexts with the aim of encouraging motivation and engagement in learning (Alsawaier, 2018; Seaborn & Fels, 2015). In physiotherapy, the gamification approach is used to enhance patient motivation and encourage greater participation in treatment. Gamified physiotherapy incorporates game dynamics (such as scoring, levels, and rewards) into physical rehabilitation processes, making exercises more enjoyable and motivating for patients (Johnson et al., 2016b; Rigby & Ryan, 2011).

In the last quarter century, as in many other fields, the rise of computer technology has also been observed in the improvement of health behaviour. Computer-based gamification encompasses various applications aimed at enabling individuals to monitor and manage their own health and well-being. (Calvo & Peters, 2014; Knight et al., 2015). One of the key areas in this regard is health games, which are used to achieve positive health outcomes. Most of these can be categorized as "health behaviour change games." These games aim to increase physical activity and support physical rehabilitation (Kharrazi et al., 2012). These games utilize various techniques such as image processing, virtual reality, augmented reality, and human-computer interaction (Johnson et al., 2016b; Morschheuser et al., 2018).

The integration of gamification in health-related interventions has garnered significant attention due to its potential to enhance engagement, motivation, and overall well-being among individuals. Gamification, defined as the application of game-design elements in non-game contexts, has shown promise in various health domains, including mental health, chronic disease management, and physical fitness (Yılmaz, 2023). One of the primary advantages of gamification is its ability to increase user engagement and adherence to health interventions. A systematic review highlighted that gamification can significantly improve adherence to web-based mental health programs, addressing a common challenge in digital health interventions (Brown et al., 2016). By incorporating elements such as points, badges, and leaderboards, gamification transforms mundane health tasks into more engaging activities, thereby motivating users to participate consistently (Davaris et al., 2021). This is particularly relevant in mental health contexts, where gamified applications have been shown to enhance personal growth and reduce stress and anxiety (Cheng et al., 2019; Johnson et al., 2016a). Furthermore, gamification facilitates behavioural change through friendly competition and social interaction. Research indicates that competitive elements can enhance motivation and collaboration among users, which are crucial for achieving health-related outcomes (Trinidad et al., 2021). For instance, gamified platforms that encourage users to compete against peers can lead to improved physical activity levels and better health outcomes (Mora-González et al., 2020). The social aspect of gamification not only promotes accountability but also creates a supportive community, which can be crucial for individuals managing chronic conditions or engaging in lifestyle changes (Gentry et al., 2019; Klaassen et al., 2018). In addition to enhancing engagement, gamification has been linked to improved health literacy and self-management skills. For example, gamified interventions have been effective in encouraging individuals to monitor their health metrics, such as glucose levels in diabetes management, thereby fostering a sense of autonomy and mastery over their health (Davaris et al., 2021; Rajani et al., 2023). This empowerment is vital for individuals facing chronic health challenges, as it encourages proactive management of their conditions. Moreover, gamification can be tailored to meet the specific needs of different populations, including adolescents and young adults. A study found that adolescents preferred robust gamification techniques, which not only increased their engagement with health apps but also led to better health outcomes (Bosworth et al., 2023). This adaptability makes gamification a versatile tool in health interventions, allowing for personalized experiences that resonate with diverse user groups (Yılmaz, 2023).

Desk work is a fundamental reality of the modern business world. However, sitting for extended hours in front of computer screens can lead to various health issues. Desk workers may experience pain in the neck, back, and shoulder regions due to prolonged sitting. Additionally, poor posture habits can eventually result in serious postural disorders (Hedge et al., 1999). Ergonomic factors such as an uncomfortable seating arrangement, improper desk height, and a computer screen positioned below eye level can cause muscle strain and pain due to prolonged sitting and continuous computer use. This can affect employees' well-being and lead to physical discomfort and productivity loss in the long term. To address these issues, ergonomic adjustments should be made, and exercises and stretches should be incorporated. Through gamified therapy, employees can perform therapeutic movements while enjoying themselves, making the experience more engaging.

This study aims to develop a web-based application that gamifies physiotherapy movements and exercises for individuals in need of physiotherapy, especially children and employees, as well as for sports enthusiasts and those aiming for active aging. The application uses image processing and artificial intelligence techniques to analyse an individual's body movements in real time. This allows a game character to move based on the player's accurate execution of specific actions, enabling them to control the game using their own body.

MATERIAL AND METHODS

Platforms Used and Hardware Requirements

During the development of the application, the Unity game engine and C# programming language were utilized for game development. Unity is a cross-platform game engine used for creating video games and simulations for computers, consoles, and mobile devices (Singh & Kaur, 2022). For compiling C# code during programming, Visual Studio 2022 was chosen. For the development of the web-based component, React was utilized. React is a JavaScript library used for building user interfaces (UI) and was developed by Facebook, featuring a component-based architecture. It helps developers create applications more efficiently and sustainably (Javeed, 2019).

For the application to function stably, a device that supports modern browsers and has an active internet connection is required, along with a standard web camera to capture the individual's image. This camera can be either an internal or a plug-and-play external camera. Additionally, a screen is needed for the individual to play the game. Apart from these features typically found on standard laptops, no extra hardware is required.

User Body Analysis

The most important stages of the application developed within this study include capturing the image through a camera and identifying body parts such as the head, arms, legs, and torso. Additionally, the eyes, nose, mouth, and facial regions are detected to facilitate movements of the head and neck. To achieve this, MediaPipe is utilized.

MediaPipe is an open-source framework developed by Google that provides a comprehensive solution for building cross-platform machine learning applications, particularly in the realm of computer vision (Figure 1).

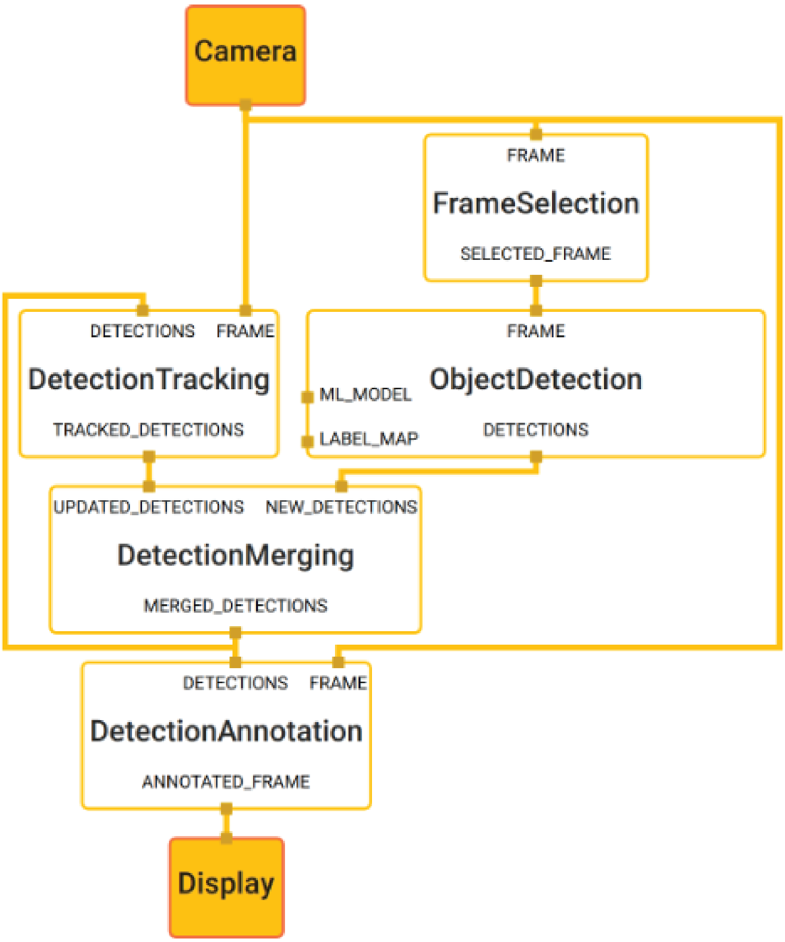

Figure 1. Object detection using MediaPipe(Lugaresi et al., 2019).

Among its various capabilities, MediaPipe Pose Detection stands out as a robust tool for real-time human pose estimation. This technology has gained traction in diverse fields, including healthcare, sports, and interactive media, due to its efficiency and accuracy in detecting key body landmarks (Figure 2). The core of MediaPipe's pose detection functionality lies in its use of Convolutional Neural Networks (CNNs) to identify and track keypoints on the human body. The framework is designed to process images and videos in real-time, making it suitable for applications that require immediate feedback, such as fitness tracking and rehabilitation exercises (Zhang, 2024). For instance, a study demonstrated the effectiveness of MediaPipe in yoga pose detection, achieving high accuracy by utilizing the Thunder version of MoveNet, which is optimized for various poses (Parashar, 2023). This ability to accurately identify poses without the need for markers significantly enhances its usability in uncontrolled environments.

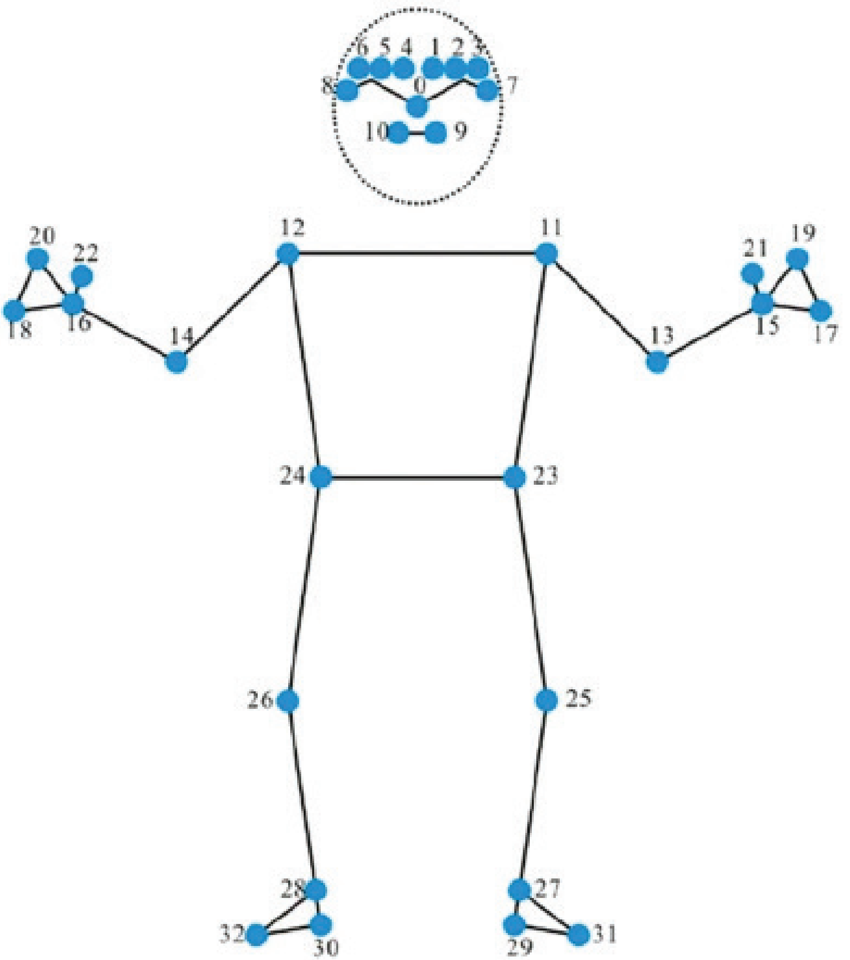

Figure 2. Landmarks marked on the human body by MediaPipe (Zhang, 2024).

In the context of healthcare, MediaPipe Pose has been utilized for assessing movement patterns in patients with conditions such as Parkinson's disease. Research has shown that the framework can effectively extract upper-limb kinematic data during deep brain stimulation procedures, thereby improving the reliability of assessments and patient outcomes (Baker et al., 2022). Furthermore, MediaPipe's capabilities extend to measuring knee flexion and extension angles in gait analysis, where it demonstrated a high correlation with traditional marker-based methods, underscoring its potential for clinical applications (Gupta et al., 2023).

The versatility of MediaPipe is also evident in its application for gesture recognition and sign language interpretation. By employing MediaPipe Hands and MediaPipe Pose, researchers have developed systems that can recognize and interpret hand gestures in real-time, facilitating communication for the hearing impaired (Šnajder & Krejsa, 2023). This integration of pose detection with gesture recognition showcases MediaPipe's adaptability across different domains, from healthcare to social interaction.

Moreover, MediaPipe's real-time performance has made it a popular choice for sports and fitness applications. For example, a study focused on taekwondo training utilized MediaPipe to analyze and provide feedback on the execution of various moves, highlighting its role in enhancing training effectiveness (Santoso, 2023)This application not only aids athletes in refining their techniques but also helps coaches monitor performance remotely.

In summary, MediaPipe Pose Detection represents a significant advancement in the field of human pose estimation, offering a flexible and efficient solution for a wide range of applications. Its integration of machine learning and computer vision technologies enables accurate real-time tracking of body movements, making it invaluable in healthcare, sports, and interactive media. As the framework continues to evolve, its potential for further innovation in human-computer interaction and motion analysis remains promising.

To ensure the complete detection of the body, the individual needs to be positioned approximately 150-300 cm away from the camera. However, when a specific body part, such as the neck or hand, needs to be activated, it is sufficient for that part to be within the camera's field of view.

APPLICATION AND FEATURES

Supported Movements

As part of the Therapinno application, consultations with physical therapy specialists, clinicians, and sports trainers identified the initial goal of supporting six different movements. These movements can be listed as follows:

Squat: The squat exercise is an integral component of strength and conditioning programs for many sports that require high levels of power, such as football, athletics, powerlifting, and Olympic weightlifting. Squats primarily strengthen key muscles involved in running, jumping, and weightlifting, including the glutes, thighs, and back muscles. It is widely believed among athletes and coaches that squats enhance athletic performance and minimize the potential for injury. The squat begins when the individual starts to lower into a squat position with their knees and hips fully extended while standing upright. The person then descends in a controlled manner until the desired depth of the squat is reached, and subsequently rises back to an upright position through a continuous motion (Escamilla, 2001). For the movement to be considered valid, the individual's knees must bend between 100° and 130° (Amico et al., 2023). This movement is illustrated in Figure 3.

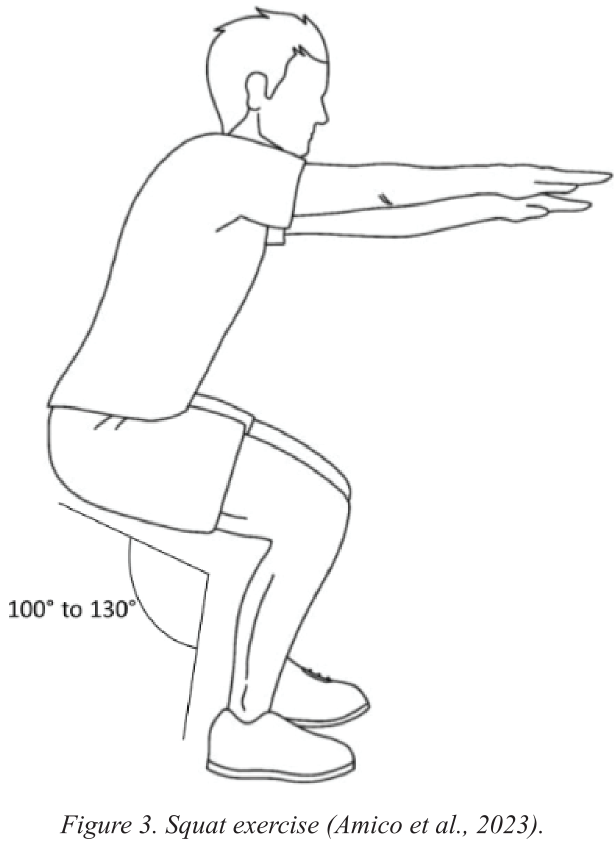

Figure 3. Squat exercise (Amico et al., 2023).

Jumping jack: Jumping jacks are a dynamic, full-body exercise that combines elements of aerobic and strength training. This exercise involves jumping into a position with the legs spread wide and the arms raised above the head, followed by a return to a standing position with the feet together and the arms at the sides. Due to their ability to elevate heart rate and engage multiple muscle groups simultaneously, including the legs, core, and shoulders, jumping jacks are commonly used in warm-up routines and high-intensity interval training (HIIT) (Machado et al., 2018; Nasci et al., 2018). The jumping jack movement is illustrated in Figure 4.

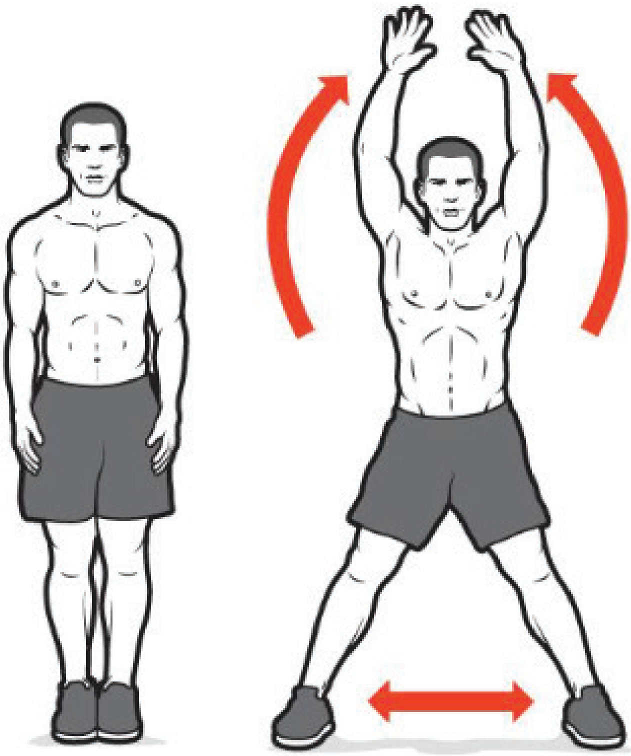

Figure 4. Jumping jack exercise (Abou Elmagd, 2020).

Cervical lateral flexion: This movement occurs when an individual tilts their head to the right and left while sitting or standing upright. For a person to be considered healthy while performing this movement, they must be able to tilt their head at least 45° or more to both the right and left sides (Swartz et al., 2005). This movement is illustrated in Figure 5.

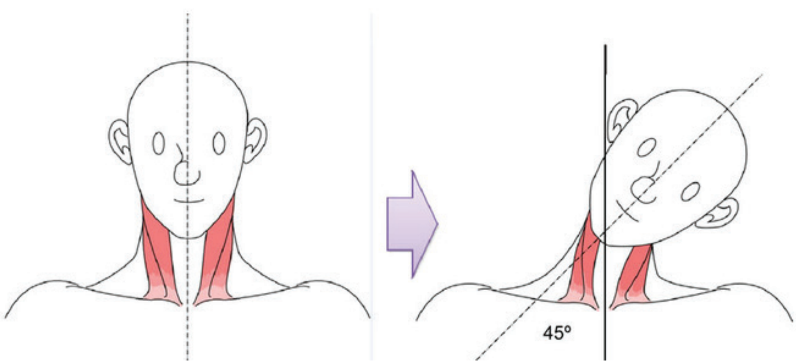

Figure 5. Cervical lateral flexion exercise (Choi et al., 2017)

Shoulder abduction/adduction: This movement occurs when the palms are pressed against the body, with the arms in a natural position, and the arm is lifted sideways without disrupting its alignment. In healthy individuals, the arm should be able to lift between 150° and 180° (*Shoulder Abduction*, n.d.). This movement is illustrated in Figure 6.

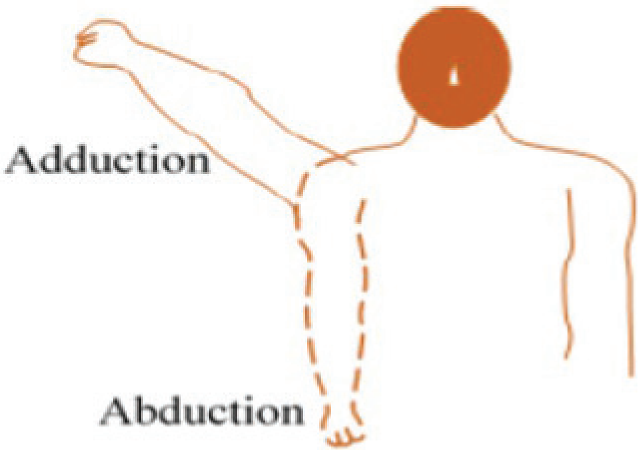

Figure 6. Shoulder abduction/adduction exercise (Assad-Uz-Zaman et al., 2020)

Lumber lateral flexion: Lumber lateral flexion refers to the movement of bending the lumbar spine to the side. This exercise typically involves standing or sitting upright while leaning to the right or left, engaging the muscles on one side of the torso. For an individual to be considered healthy, they should be able to flex their torso laterally to approximately 35° or more on either side. This movement is important for assessing flexibility and strength in the lower back and can contribute to overall core stability (McGregor et al., 1995). This movement is illustrated in Figure 7.

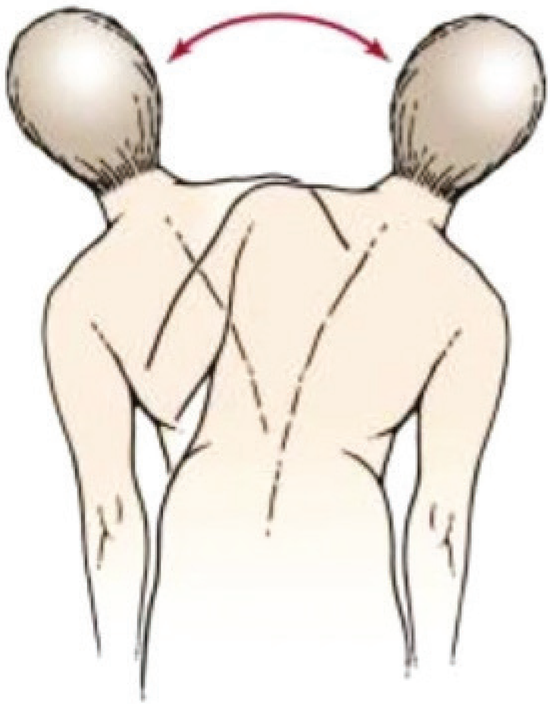

Figure 7. Lumber lateral flexion exercise (Almoallim et al., 2021)

Balance exercise: Many injuries and medical conditions can affect balance. For instance, an ankle sprain can lead to balance disturbances due to tears in the soft tissue that transmit balance inputs to the brain. Individuals who have experienced a stroke often face significant balance issues that complicate walking. In such cases, balance exercises are recommended. The balance exercise included in this study is illustrated in Figure 8.

Figure 8. Balance exercise (Pojskic et al., 2020)

Designed Games

In this study, four different interactive games have been designed: “Running Codi,” “Break Bricks,” “Red vs. Black,” and “Ant Kiki.” When users access the application page, they are presented with cards from which they can select the exercise they wish to perform. (Figure 9). The user selects one of these cards to proceed to the next stage. In the subsequent stage, a screen appears where the user can choose a game (Figure 10).

Figure 9. Exercise selection screen.

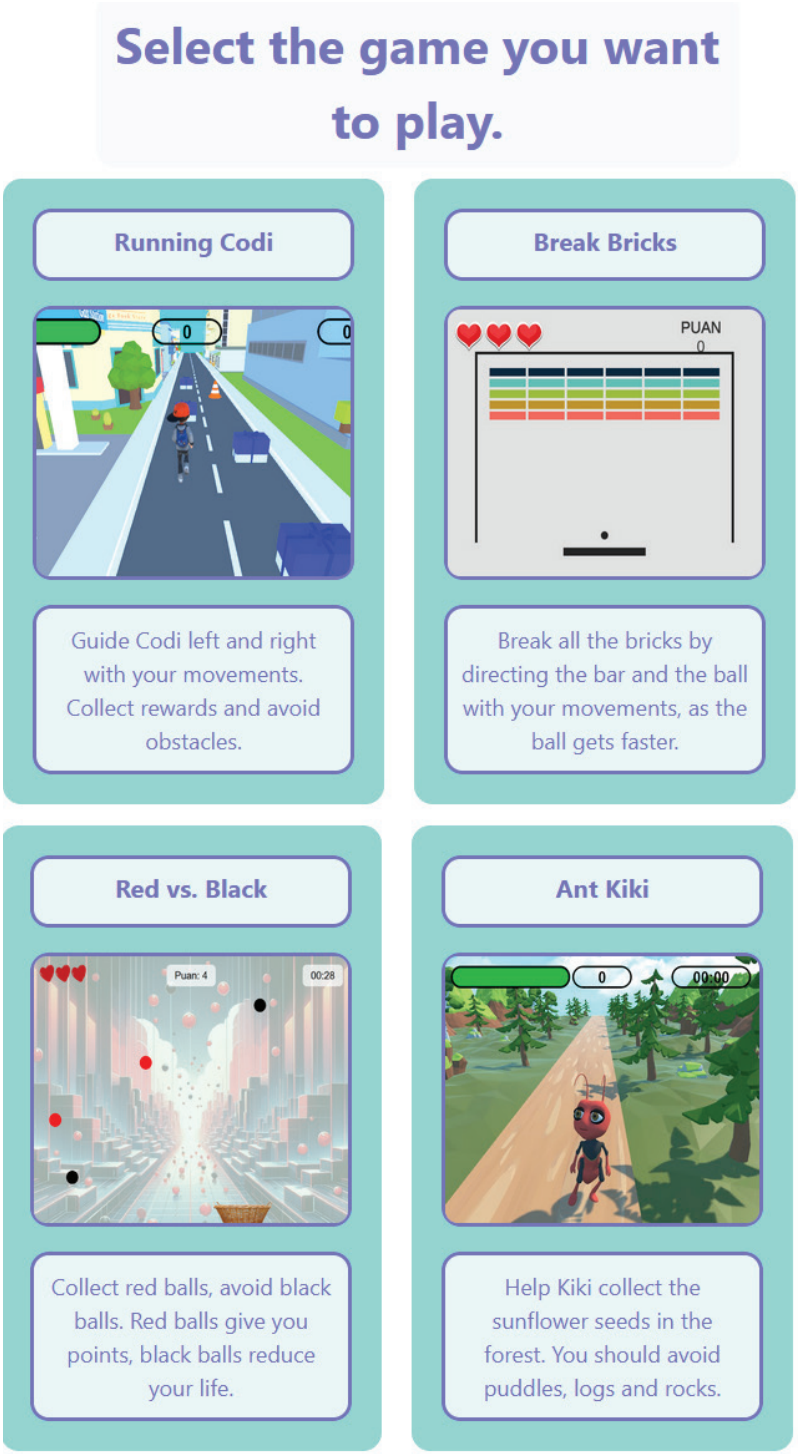

Figure 10. Game selection screen.

After the user selects their desired movement and game, they must grant the necessary camera permissions prompted by the browser. Once the camera begins capturing video, the user's body analysis starts and continues in real-time. If the user wishes to restart the game, they simply need to raise their hands above their head and clap.

The details of each game and the movements the game supports are as follows:

Running Codi: In this game, the main character is a child named Codi, who runs through streets while encountering various orange-colored obstacles along the way. During the gameplay, the player is allowed to collide with these obstacles up to three times. Upon the fourth collision, the game resets, displaying the total score and the time spent playing. To earn points, the player must collect blue-colored rewards scattered throughout the course. The character can be moved to the right or left by the player to avoid obstacles and gather rewards.

The game incorporates four specific exercises: shoulder abduction/adduction, lumbar lateral flexion, cervical lateral flexion, and balance exercises. It is particularly recommended for new users of the application, as well as individuals undergoing physical therapy. As the game progresses, the character's speed increases, and the number of obstacles rises, making the gameplay more challenging. The highest score and longest playtime are stored on the server and displayed each time the game is launched.

The game is designed to support rehabilitation exercises, providing an interactive and engaging method for users to perform physical therapy movements. An example of a user performing the cervical lateral flexion exercise is shown in Figure 11. This gameplay screenshot demonstrates how the game's mechanics can be used to enhance rehabilitation by integrating physical movement with entertainment.

Figure 11. A gameplay screenshot of the Running Codi game.

Break Bricks: In this game, a classic block-breaking concept is implemented, where the player must control a paddle and guide the ball to break blocks in order to score points and progress to subsequent levels. As the ball hits the blocks, the blocks are destroyed, and the player earns points. The ball bounces off the blocks and the game stage's walls in accordance with the laws of physics. If the player fails to catch the ball with the paddle, one life is lost. The game ends when the player loses a total of three lives. The paddle is controlled by the player, who moves it left or right to strike the ball and continue the game.

This game integrates four specific exercises: shoulder abduction/adduction, lumbar lateral flexion, cervical lateral flexion, and balance exercises, making it a valuable tool for physical therapy and rehabilitation. As the number of blocks decreases, the speed of the ball incrementally increases, making the gameplay progressively more challenging. The highest score and the longest time played are stored on the server and displayed each time the game is launched.

This game is designed to support rehabilitation exercises, offering users an engaging and interactive method to perform therapeutic movements.

Figure 12 provides a screenshot of a user performing a shoulder abduction/adduction exercise while playing the game, demonstrating how the game mechanics can be utilized to combine physical activity with an enjoyable gaming experience.

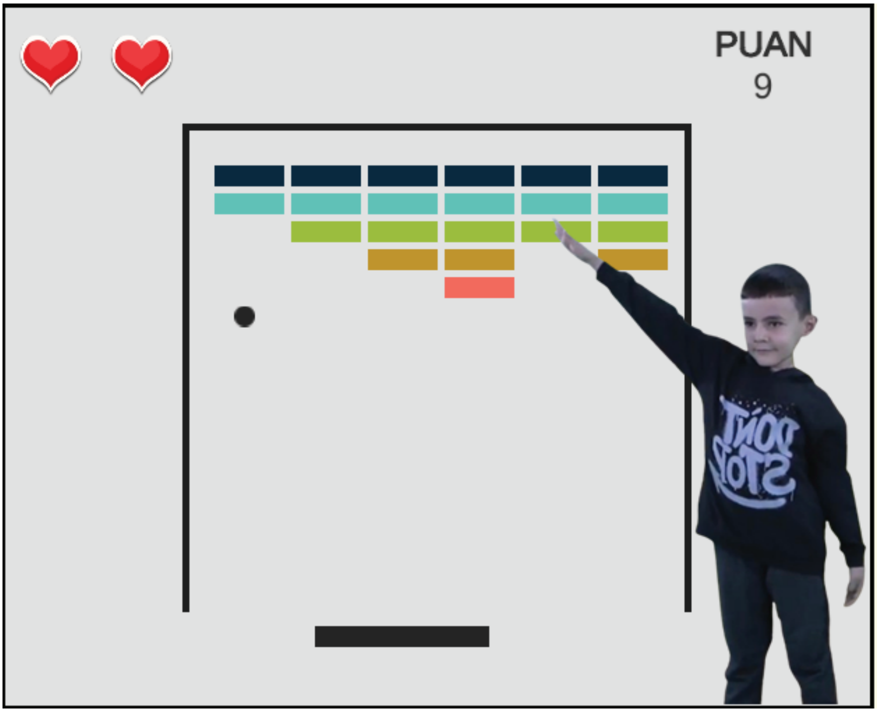

Figure 12. A gameplay screenshot of the Break Bricks game.

Red vs. Black: In this game, black and red balls are in competition, and the objective is to collect the red balls using a basket while avoiding the black balls. Both red and black balls randomly fall from the top of the screen from various coordinates. The player controls the basket at the bottom of the screen, moving it left and right to catch the red balls and dodge the black ones. Every time a black ball lands in the basket, the player loses one life, with a total of three lives available. As the player collects red balls, their score increases.

As time progresses, the difficulty level of the game increases, and the balls fall at a faster rate, adding to the challenge. The game is played by moving the basket left or right, allowing the player to engage in real-time, dynamic gameplay.

This game supports four specific rehabilitation exercises: shoulder abduction/adduction, lumbar lateral flexion, cervical lateral flexion, and balance exercises. It offers a unique and interactive way to integrate physical therapy movements into gameplay, making it suitable for users in rehabilitation or those new to the application.

The highest score and longest playtime are stored on the server and displayed to the user each time the game is launched. A screenshot of a user performing a lumbar lateral flexion exercise while playing the game is provided in Figure 13, showcasing how the game's mechanics can be utilized to facilitate physical rehabilitation in an engaging manner.

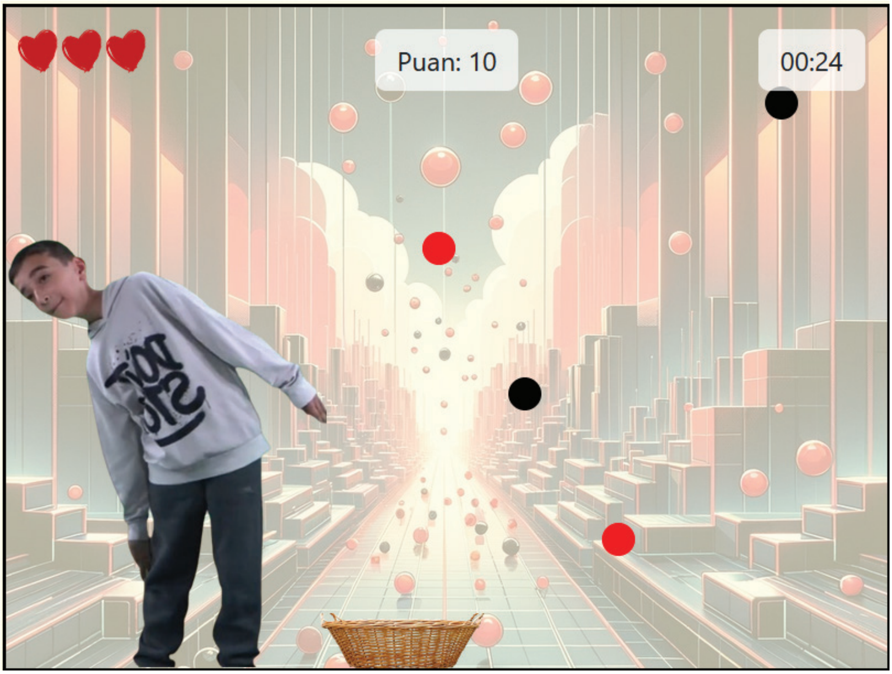

Figure 13. A gameplay screenshot of the Red vs. Black game.

Ant Kiki: In this game, the character is an ant named Kiki, a creature of nature. Unlike other games, this one features a more complex environment with multiple obstacles. While most games typically have a single type of obstacle, this game includes three distinct ones: puddles, logs, and rocks. Kiki's objective is to collect sunflower seeds as it runs through the environment. The player guides the ant using physical body movements to help it navigate the obstacles. The game also incorporates sound effects, enhancing the immersive experience.

This game supports a wide range of movements, including abduction/adduction, lumbar lateral flexion, cervical lateral flexion, balance exercises, squats, and jumping jacks, making it highly versatile in terms of physical engagement. To jump over a puddle, the player must lift their leg or perform a jumping jack, depending on the selected movement. To slide under a log, the player must perform a squat. Each obstacle reduces the player's health by a different degree, but red hearts scattered throughout the game can restore lost health. When the health bar, located in the top-left corner of the screen, is depleted, the game ends, and the player's total score and time spent playing are displayed. The highest score and longest playtime are stored on the server and shown to the player each time the game is launched.

This game is particularly demanding in terms of physical effort, making it more suitable for healthy individuals who may not necessarily require physical therapy. It provides a fun and engaging way to exercise. A screenshot of a user performing a balance exercise while playing the game is shown in Figure 14, highlighting how the game can be used to encourage physical activity in an interactive format.

Figure 14. A gameplay screenshot of Ant Kiki game.

Running the Application and Playing the Games

The Therapinno application consists of three main stages: capturing the image, identifying the body/limbs, and controlling the game character's movements. The workflow of the Therapinno application is presented in Figure 15.

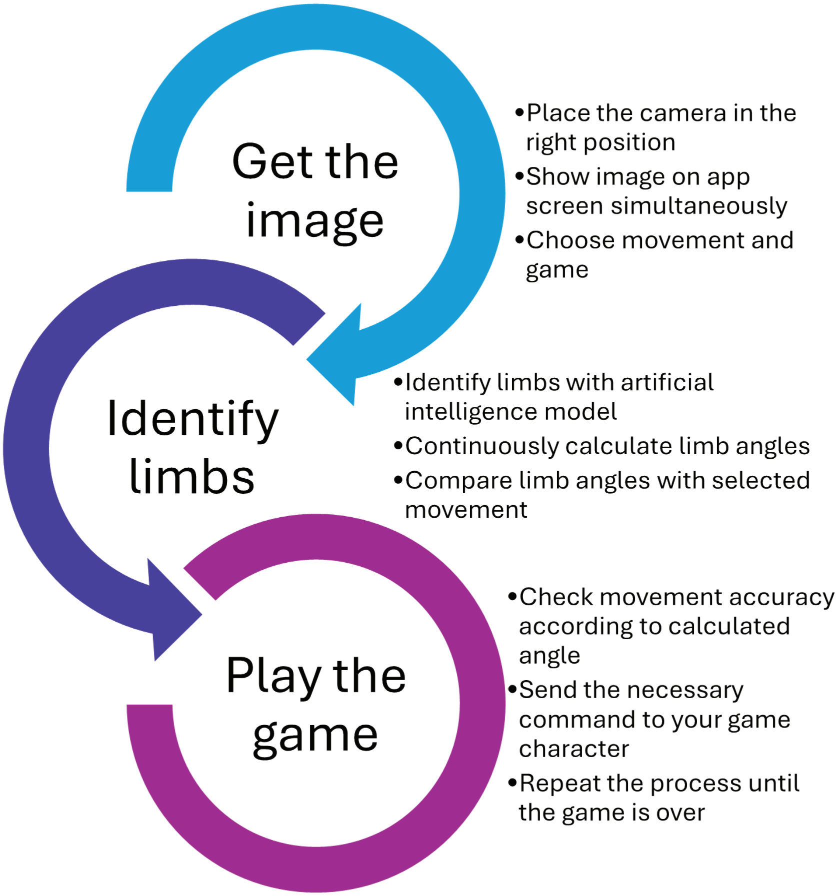

Figure 15. Therapinno app workflow.

In the first stage, the camera is positioned correctly, the image is displayed in real-time on the application screen, and the game/exercise is selected. In the second stage, a body and limb detection is performed using an AI-supported model, limb angles are continuously monitored, and the calculated angles are compared based on the selected exercise. In the third stage, the accuracy of the movement is checked according to the calculated angle, the necessary command (e.g., moving left or right, jumping, bending) is sent to the game character, and the process is repeated until the game is completed.

The image is captured in real-time via the camera and processed frame by frame. During this process, no delay occurs, and an average of

20-24 frames per second is captured. The captured images are processed using the AI-based MediaPipe, enabling the detection of the body and limbs. As shown in Figure 16, the coordinates of the required areas for the application, including the head, face, torso, arms, waist, legs, and feet, are continuously recorded.

Subsequently, the limb angles (d) are calculated based on the selected movements. For instance, for an individual performing shoulder adduction, the tilt of the torso is computed by averaging the x-coordinates (horizontal) of the shoulders and knees when the body is in a natural position, as described in Equation 1. Then, the angle of the arm is calculated using the coordinates of the shoulder, elbow, and wrist, again using Equation 1 to determine the arm's tilt. In this way, the shoulder angle is obtained. If the shoulder angle is 150° or more, the movement is considered correct, allowing the game character to be guided accordingly. This ensures that the game character progresses and earns points based on the correct execution of all movements.

$$d = \tan^{-1}\left(\frac{y_2 - y_1}{x_2 - x_1}\right) * \frac{180}{\pi} \tag{1}$$

Figure 16. Finding and displaying the coordinates required to determine the limbs from the images taken.

All these processes occur simultaneously, with image capture, limb detection, angle calculation for relevant limbs, and game character control based on the accuracy of movement angles being completed in approximately 42-50 milliseconds. This ensures that the game character moves in real-time with the user's body, without any noticeable delay.

CONCLUSIONS

In this study, an interactive, gamified, web-based exercise application called "**Therapinno**" has been developed. **Therapinno** application aims to transform exercise into an enjoyable activity, enabling individuals to complete their therapy and exercises while playing games. The application utilizes artificial intelligence to analyze the body in real-time from video input and automatically calibrates according to the individual's body size. Both adults and children can use the application without requiring any additional settings. It can be utilized with full-body movements while standing or with neck movements only. The application supports six different movements and includes four different games. Game characters are controlled in real-time based on the user's body movements. It does not require any additional hardware such as game controllers, operating solely with a standard webcam. This makes the application both accessible and cost-effective compared to many other applications. Additionally, it can function without the need for a green or blue screen, operating effectively under various lighting conditions. The accuracy of the exercises performed, the time spent on each exercise, and the quality of the movements are recorded. The established infrastructure allows for the easy addition of new games and exercises.

The developed gamified physiotherapy application represents a promising intersection of healthcare and digital technology by leveraging advanced image processing and artificial intelligence techniques such as MediaPipe. By integrating game mechanics into physical rehabilitation exercises, this approach enhances patient engagement, making therapy not only more enjoyable but also more accessible. The use of real-time body analysis enables users to control game characters with their movements, promoting the accurate execution of therapeutic exercises. This application serves a broad audience, including children, employees, sports enthusiasts, and those aiming for active aging, providing an innovative and effective means of managing and improving physical health.

As the healthcare sector continues to explore the possibilities of artificial intelligence and gamification, the importance of personalized, adaptive interventions is becoming increasingly evident. The capability to track body movements in real-time and provide feedback based on user performance underscores the role of AI in delivering tailored health interventions. By harnessing these technologies, the application not only contributes to the rehabilitation process but also supports the broader objective of promoting an active and healthy lifestyle through engaging, user-friendly platforms.

Plans for further development include making the application more compact and supporting mobile platforms. Future work will also focus on utilizing artificial intelligence to control game characters and adding various character options. The target audience of the application is broad, encompassing chronic physiotherapy patients, children, physiotherapists, desk workers, individuals in recovery, athletes, the elderly, wellness enthusiasts, and educational institutions. Ongoing studies aim to clinically assess the effectiveness of the application. As artificial intelligence and gamification continue to evolve, their application in healthcare interventions holds substantial promise for improving patient outcomes and enhancing overall quality of life.

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DIABETES RISK PREDICTION WITH ARTIFICIAL INTELLIGENCE: A WEB-BASED APPLICATION

This part presents the development of a web-based artificial intelligence application that enables individuals to calculate their diabetes risk. The system uses routine laboratory test results and daily lifestyle habits provided by users to predict diabetes risk. Several machine learning algorithms (KNN, Logistic Regression, CatBoost, Random Forest, SVM, Multilayer Perceptron, and Deep Neural Networks) were evaluated, and the best-performing model was selected. The Deep Neural Network (DNN) model achieved the highest accuracy and was integrated into a web interface for end-user accessibility. This study demonstrates the practical application of AI-based early diagnosis and paves the way for preventive interventions in personal healthcare management.

INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels (hyperglycemia) due to defects in insulin secretion, insulin action, or both. The disease is primarily classified into two main types: Type 1 diabetes (T1D) and Type 2 diabetes (T2D). T1D is an autoimmune condition that typically manifests in childhood or adolescence, leading to the destruction of insulin-producing beta cells in the pancreas. In contrast, T2D is more prevalent in adults and is often associated with insulin resistance and relative insulin deficiency, frequently linked to obesity and sedentary lifestyles (Balkau et al., 2011; Yamaguchi et al., 2016).

The incidence of T1D is notably high among children and adolescents, accounting for approximately 85% of diabetes cases in individuals under 20 years old, with a peak incidence between ages 10 and 14 (Yamaguchi et al., 2016). However, it is increasingly recognized that T1D can also manifest in adults, with more than half of new cases occurring in this population (Leslie et al., 2021). This phenomenon has led to the identification of atypical presentations of diabetes, where patients may initially be misdiagnosed with T2D due to their clinical characteristics, only to later confirm T1D through antibody testing (Knopp & Perumareddi, 2021). Such misclassification can complicate treatment and management strategies, highlighting the necessity for accurate diagnostic criteria (Leslie et al., 2021).

Recent studies have also shed light on the concept of "double diabetes," where individuals with T1D exhibit features of insulin resistance typically associated with T2D. This condition is characterized by significant weight gain, increased insulin requirements, and a family history of T2D (Cleland et al., 2013; Connelly et al., 2015). The presence of insulin resistance in T1D patients can lead to an increased risk of complications, including cardiovascular disease and diabetic kidney disease, even in cases where glycemic control appears adequate (Ahlqvist et al., 2018; Rosengren & Dikaiou, 2023). This underscores the importance of comprehensive management strategies that address both glycemic control and associated metabolic abnormalities. Moreover, diabetes has been linked to increased susceptibility to infections and higher mortality rates, particularly in the context of COVID-19. Individuals with T1D have been found to have a significantly higher risk of pneumonia and related complications, which may contribute to the observed excess mortality associated with diabetes during the pandemic (Barron et al., 2020; McGurnaghan et al., 2021). This highlights the need for vigilant monitoring and preventive strategies in diabetic populations, especially during public health crises.

The diagnosis of diabetes mellitus is a critical aspect of managing this chronic condition, which is characterized by elevated blood glucose levels. The diagnostic process involves a combination of clinical assessment, laboratory tests, and adherence to established criteria. The American Diabetes Association (ADA) and the World Health Organization (WHO) provide guidelines that define diabetes based on specific thresholds for blood glucose levels, including fasting plasma glucose (FPG), oral glucose tolerance test (OGTT), and glycated hemoglobin (HbA1c) (Tosur, 2024). Moreover, the prevalence of undiagnosed diabetes is a significant concern, with studies indicating that a substantial proportion of individuals may remain unaware of their condition until complications arise (Cigolle et al., 2022). For instance, research has shown that in certain populations, the prevalence of undiagnosed diabetes can be as high as 27% to 32% among stroke patients, underscoring the importance of routine screening in clinical settings (Lau et al., 2018). Additionally, the delay in diagnosis can lead to increased healthcare costs and complications, highlighting the need for timely identification and management of diabetes (Shrestha et al., 2018).

The application of machine learning (ML) in the diagnosis of diabetes has gained significant attention in recent years due to its potential to enhance predictive accuracy and facilitate early detection. Machine learning algorithms can analyze complex datasets, identifying patterns and relationships that may not be apparent through traditional statistical methods. This capability is particularly valuable in the context of diabetes, where early diagnosis can lead to better management and prevention of complications. One of the key advantages of machine learning in diabetes diagnosis is its ability to handle large and diverse datasets. For instance, a study by Cahn et al. demonstrated the development and validation of a machine learning model that predicts the progression from prediabetes to diabetes, utilizing electronic health records from various populations (Cahn et al., 2020). This model outperformed traditional linear models by capturing subtle multivariate relationships, which are crucial for accurate risk assessment. The ability to analyze large datasets allows for more generalizable findings, which is essential for effective public health interventions (Wang & Jiang, 2023). Similarly, Razavian et al. explored population-level predictions of Type 2 diabetes using claims data, illustrating how machine learning can identify risk factors and enhance early detection strategies (Razavian et al., 2015). These studies underscore the transformative potential of machine learning in diabetes care, particularly in identifying at-risk individuals before the onset of the disease. In addition to predictive modeling, machine learning has been applied in the classification of diabetes-related complications. For example, Gulshan et al. developed a deep learning algorithm for the detection of diabetic retinopathy from retinal fundus photographs, achieving high sensitivity and specificity (Gulshan et al., 2016). This application not only aids in the timely diagnosis of a common complication of diabetes but also exemplifies how machine learning can be integrated into clinical workflows to enhance patient outcomes. Moreover, the comparative analysis of various machine learning algorithms has been a focal point in diabetes research. Studies have compared the performance of different classifiers, such as decision trees, support vector machines, and neural networks, to determine the most effective approach for diabetes prediction (Kandhasamy & Balamurali, 2015; Shah, 2024). This comparative research is essential for refining diagnostic tools and ensuring that healthcare providers have access to the most effective technologies for managing diabetes.

In conclusion, the integration of machine learning into diabetes diagnosis represents a significant advancement in healthcare technology. By leveraging the capabilities of machine learning algorithms, healthcare professionals can improve the accuracy of diabetes predictions, facilitate early detection, and enhance the management of this chronic disease. Effective screening strategies are essential to identify at-risk populations and facilitate early intervention, ultimately reducing the burden of diabetes and its associated complications.

This study aims to develop a web-based platform that assesses an individual's risk of developing diabetes by analyzing their laboratory blood test results and daily lifestyle habits. The project employs various popular machine learning algorithms on the dataset, ultimately integrating the highest-performing model into the web interface for real-time risk prediction.

MATERIALS AND METHODS

Dataset Used and Data Pre-Preparation Procedures

In this study, a publicly available dataset, which can be used for developing and testing machine learning applications, was utilized. The relevant dataset was obtained from the Kaggle platform. Kaggle is a data science platform that hosts competitions for business problems, academic research, or recruitment purposes (Bojer & Meldgaard, 2021). The obtained dataset consists of 5 categorical variables: gender, hypertension, heart disease, smoking history, and diabetes status, as well as 4 numerical columns: age, BMI, HbA1c level, and blood glucose level. The dataset contains approximately 54,000 rows across a total of 9 columns. However, upon examination, it was observed that certain labels in some columns were disproportionately represented. For instance, in the diabetes status column, which will be used as the output in this study, there are around 7,000 rows with a value of 1, whereas approximately 47,000 rows have a value of 0. This indicates that the dataset is imbalanced. To address this issue, the undersampling technique was applied. Undersampling is a data preprocessing technique primarily used to address class imbalance in datasets, particularly in machine learning contexts. This method involves reducing the number of instances in the majority class to balance the dataset with the minority class. The primary objective of undersampling is to enhance the performance of classification algorithms by mitigating the bias that arises from imbalanced data distributions (Mathews & Hari, 2018; Sowah et al., 2016). Several undersampling techniques have been developed to improve the effectiveness of this approach. Random undersampling is the simplest method, where instances from the majority class are randomly removed until a desired balance is achieved. After applying this method, a much more balanced dataset was obtained. The distribution of the categorical variables in the dataset is shown in Figure 1.

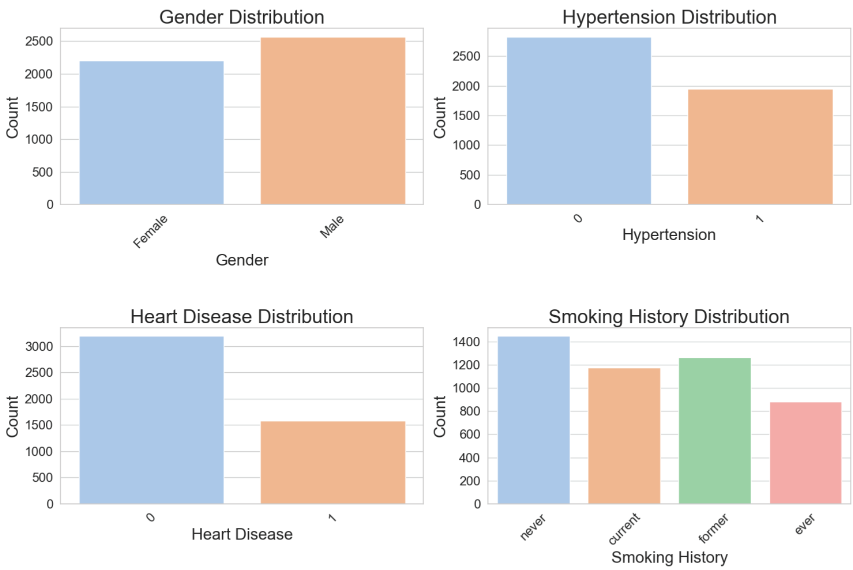

Figure 1. Distribution of categorical data.

Various distribution analyses were also conducted on the numerical data. The density distribution graph for these variables is presented in Figure 2.

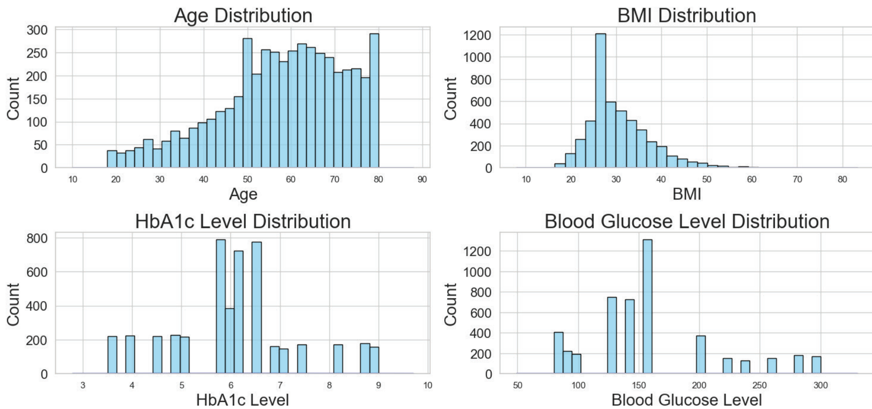

Figure 2. Distribution of numerical data.

The correlation coefficients among all the variables were examined. The highest positive correlation was found between HbA1c level and diabetes status, with a value of 0.61. The correlations between diabetes status and blood glucose level, BMI, and age were calculated as 0.53, 0.21, and 0.17, respectively. The correlation matrix of all the features is presented in Figure 3. In the final version of the dataset, there are 8 features to be used as inputs and 1 feature to be used as the output. Among the input features, 4 are categorical, and 4 are numerical. First, the categorical variables were encoded. Then, min-max normalization was applied to the numerical variables. This prepared the data for input. No changes were made to the "Diabetes status" column, which will be used as the output.

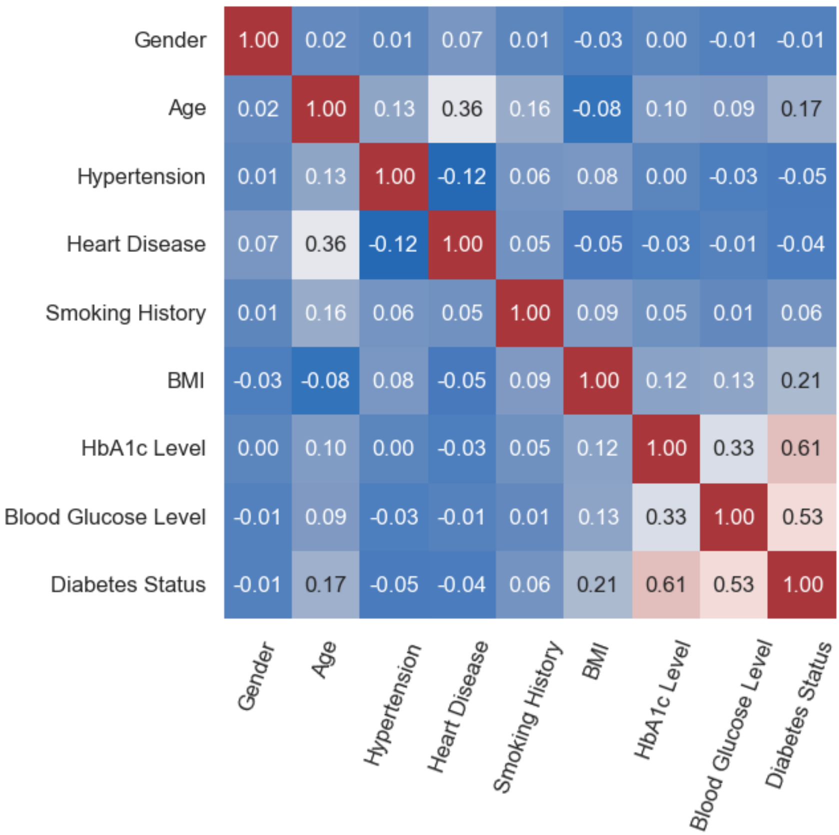

Figure 3. Correlation values between data.

Programming Environment

The processing of the dataset, data preprocessing, the development of the artificial neural network model, and the calculation of the weights were performed on a computer with an Intel i7 processor and 16 GB of RAM, using the Python programming language. For the design of the webpage, HTML, CSS, and JavaScript were used.

Metrics Used in Performance Measurement

In the field of machine learning, particularly in classification tasks, it is crucial to evaluate the performance of models using various metrics. These metrics provide insights into how well a model is performing and help in comparing different models. Key metrics include accuracy, sensitivity, specificity, F1 score, confusion matrix, and the Receiver Operating Characteristic (ROC) curve.

The confusion matrix is a fundamental tool for evaluating the performance of a classification algorithm. It is a table that summarizes the performance of a classification model by comparing the predicted classifications to the actual classifications. The matrix consists of four components:

True Positives (TP): The number of instances correctly predicted as positive.

True Negatives (TN): The number of instances correctly predicted as negative.

False Positives (FP): The number of instances incorrectly predicted as positive (Type I error).

False Negatives (FN): The number of instances incorrectly predicted as negative (Type II error) (Salih & Abdulazeez, 2021; Tharwat, 2020)

Accuracy is the ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances. It is calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Sensitivity, also known as recall, measures the proportion of actual positives that are correctly identified. Sensitivity is particularly important in medical diagnostics, where failing to identify a positive case (e.g., a disease) can have serious consequences (Kaur et al., 2022). It is calculated as:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity measures the proportion of actual negatives that are correctly identified. Specificity is crucial in scenarios where false positives can lead to unnecessary interventions or anxiety (Kaur et al., 2022). It is calculated as:

$$Specificity = \frac{TN}{TN + FP}$$

The F_1 score is the harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful when dealing with imbalanced datasets. The F_1 score ranges from 0 to 1, with 1 indicating perfect precision and recall (Hejmanowska et al., 2021). The F_1 score is calculated as:

$$F_1 Score = \frac{2 * TP}{2 * TP + FP + FN}$$

The ROC curve is a graphical representation of a classifier's performance across different threshold settings. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1 - specificity). The area under the ROC curve (AUC) provides a single measure of overall performance, with higher values indicating better model performance (Saito & Rehmsmeier, 2015).

EXPERIMENTAL STUDY

Train/Test Split and Grid Search

The train-test split is a fundamental concept in machine learning that significantly influences the performance and generalization of predictive models. One critical aspect of train-test splitting is its impact on model generalization. Studies have shown that using a single random train-test split can lead to a generalization gap, where the model performs well on the training data but poorly on unseen test data (Decoux et al., 2023). The choice of split ratio is also a topic of considerable debate. Traditional practices often default to ratios such as 70:30 or 80:20 for training and testing, respectively (Jjagwe et al., 2023).

The performance of machine learning models is often contingent upon the choice of hyperparameters—settings that govern the learning process. Hyperparameter tuning is essential for optimizing model performance, and grid search has emerged as a popular technique for this purpose. Grid search is a systematic method for hyperparameter optimization that involves defining a grid of hyperparameter values and evaluating the model's performance for each combination. Grid search is particularly advantageous due to its exhaustive nature, ensuring that all combinations are considered. However, it can be computationally expensive, especially with a large number of hyperparameters or extensive value ranges (Decoux et al., 2023)

In this study, the dataset was split into a 70:30 ratio for all algorithms used. While 70% of the data was randomly allocated for training, 30% was used for testing. Additionally, grid search was applied to cover all possible parameters for each algorithm, and the optimal hyperparameters were identified.

Algorithms Used

In this study, seven different algorithms commonly used in classification problems were selected, and their results are presented below.

K Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN) is a popular machine learning algorithm that falls under the category of supervised learning and belongs to the family of instance-based learning methods. It is included in many machine learning libraries and is widely used for classification tasks due to its simplicity and effectiveness. This classifier operates on the principle of the k-nearest neighbors (k-NN) algorithm, which classifies a data point based on the majority class of its k closest neighbors in the feature space. The algorithm assumes that similar instances are located close to each other, which is a fundamental characteristic of many real-world datasets (Mathews & Hari, 2018; Sowah et al., 2016). The model does not explicitly learn from the training data. Instead, it stores the training instances in memory. This characteristic makes KNN a lazy learner, as it defers computation until a query instance is presented (H. Guo et al., 2019). To determine the "closeness" of instances, the algorithm employs a distance metric. The most commonly used distance metric is the Euclidean distance, but other metrics such as Manhattan distance, Minkowski distance, and Hamming distance can also be utilized depending on the nature of the data (Polvimoltham & Sinapiromsaran, 2021). When a new instance needs to be classified, the algorithm computes the distance between the new instance and all training instances. It then selects the k nearest neighbors based on the chosen distance metric. The class label of the new instance is assigned based on a majority vote among the k neighbors (Dal Pozzolo et al., 2015). The algorithm can be easily adapted to multi-class classification problems and can handle both numerical and categorical data. However, the algorithm can be computationally expensive, especially with large datasets, as it requires calculating the distance to all training instances for each query instance (Akçakaya et al., 2014; Y. Guo et al., 2017)

The KNN classifier is a powerful and intuitive classification algorithm that is widely used in machine learning. Its simplicity and effectiveness make it a popular choice for various applications, despite its limitations in terms of computational efficiency and sensitivity to noise. Understanding the underlying principles and characteristics of the KNN classifier is essential for practitioners and researchers aiming to leverage its capabilities in real-world scenarios.

In this application, the optimal value for K was found to be 7. As a result of the KNN algorithm, the accuracy, sensitivity, specificity, and F_1 score were determined to be 81.70%, 76.42%, 85.93%, and 0.79, respectively. The confusion matrix for this algorithm is presented in Figure 4. This matrix illustrates the correct and incorrect classifications made by the model.

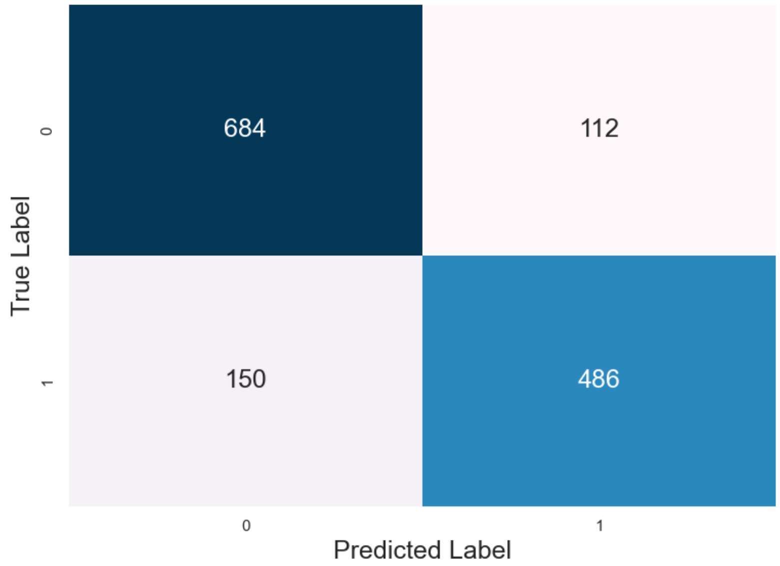

Figure 4. Confusion matrix resulting from the K Nearest Neighbors method.

To gain a better understanding of the model's performance, the ROC curve was plotted (Figure 5). The ROC curve illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various classification thresholds. The ROC AUC value of the model was calculated to be 0.91. This result indicates that the model is highly successful in its classification task and possesses a strong discriminative ability.

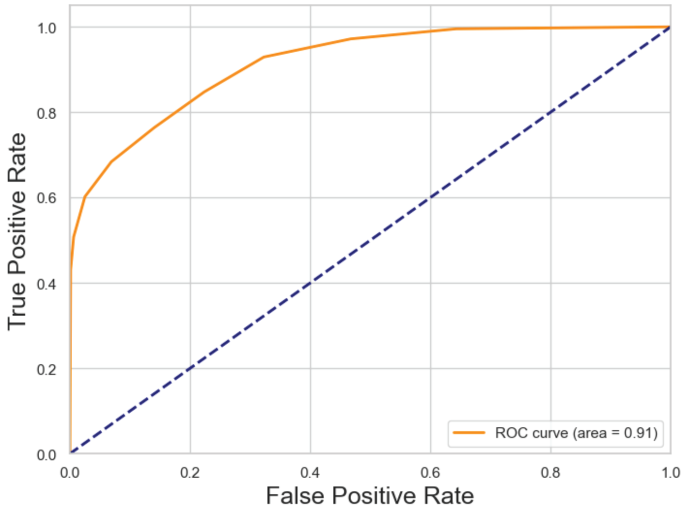

Figure 5. The ROC curve resulting from the K Nearest Neighbors method.

Logistic Regression (LR)

Logistic regression (LR) is a widely used statistical method for binary classification problems, where the objective is to model the probability of a binary outcome based on one or more predictor variables. It is particularly effective in scenarios where the relationship between the dependent variable and independent variables is not strictly linear, making it a versatile tool in various fields, including medicine, finance, and social sciences (Blagus & Lusa, 2013; Van Den Goorbergh et al., 2022). One of the significant challenges in applying LR is dealing with class imbalance, where one class is significantly underrepresented compared to the other. This imbalance can lead to biased estimates and poor predictive performance, as the model may become overly tuned to the majority class (Cartus et al., 2020; Pias et al., 2023). Various techniques, such as undersampling the majority class or oversampling the minority class, are often employed to mitigate this issue (Xie & Xu, 2024). LR is successfully utilized in various fields, including medical diagnosis, credit scoring, and marketing. It is computationally efficient and capable of handling large datasets, making it suitable for real-time applications. However, the model can be sensitive to outliers, which may distort results and lead to erroneous predictions (Van Den Goorbergh et al., 2022).

LR remains a foundational technique in statistical modeling and machine learning, particularly for binary classification tasks. Its ability to provide interpretable results and handle various types of data makes it a valuable tool across multiple domains. However, practitioners must be aware of its limitations, particularly regarding class imbalance and the assumptions underlying the model, to ensure robust and reliable predictions.

The LR algorithm utilizes three parameters: the C coefficient, the penalty parameter, and the solver. The C coefficient is used to prevent overfitting and represents the regularization strength. The penalty specifies which type of regularization to use, allowing for options such as L1 (Lasso) or L2 (Ridge). The solver refers to the optimization algorithm used. For this study, the optimal C coefficient was set to 0.01, the penalty value was chosen as L2, and the solver was selected as "liblinear." As a result of the LR algorithm, the accuracy, sensitivity, specificity, and F_1 score were determined to be 84.85%, 80.19%, 88.57%, and 0.82, respectively. The confusion matrix for this algorithm is presented in Figure 6.

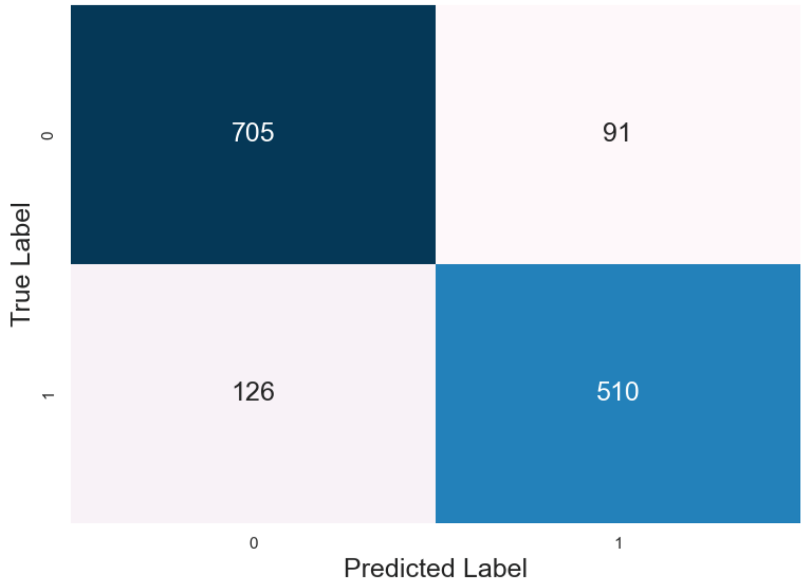

Figure 6. Confusion matrix of the Logistic Regression method.

To evaluate the model's performance, the ROC curve was generated (Figure 7). The ROC curve allows for a more comprehensive assessment of the classification ability. The calculated ROC AUC value was found to be 0.94. This high value indicates that the model operates effectively in its classification task and provides a clear distinction between the two classes. The high ROC AUC further supports the reliability and success of the model.

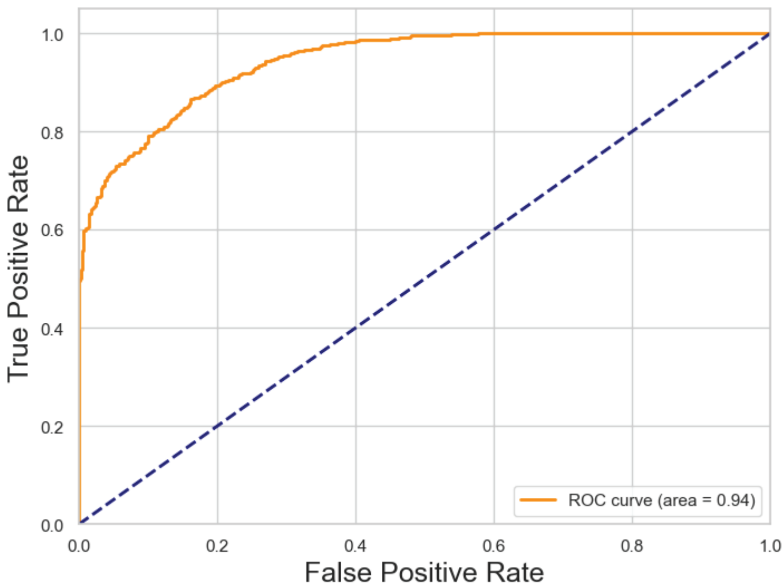

Figure 7. ROC curve of the Logistic Regression method.

CatBoost (CB) Classifier

CatBoost (CB) classifier is a powerful machine learning algorithm developed by Yandex, designed for gradient boosting on decision trees. It is particularly notable for its ability to handle categorical features directly, which sets it apart from other gradient boosting frameworks like XGBoost and LightGBM that require preprocessing of categorical variables. This capability makes CatBoost highly efficient and user-friendly, especially in applications involving datasets with a significant number of categorical features (Dorogush et al., 2018).

One of the standout features of CB is its implementation of "ordered boosting," which helps to reduce overfitting and improve the model's generalization capabilities. This technique involves using a permutation-based approach to create a more robust training process by considering the order of data points during training (Dorogush et al., 2018). Additionally, CB employs a unique method for handling categorical variables, which allows it to automatically encode these features without the need for manual preprocessing, thus simplifying the modeling pipeline (Ibrahim et al., 2023).

CB classifier has demonstrated competitive performance across various domains, including finance, healthcare, and cybersecurity. For instance, in the context of predicting cardiac surgery-associated acute kidney injury, CB achieved impressive ROC-AUC scores, showcasing its effectiveness in medical applications (Q. Li et al., 2023). Furthermore, it has been successfully utilized in detecting botnet attacks, highlighting its versatility in cybersecurity applications (Hajjouz & Avksentieva, 2023).

In summary, CB classifier is a robust and versatile machine learning algorithm that excels in handling categorical data and mitigating overfitting through its ordered boosting technique. Its application across various fields, including healthcare, finance, and cybersecurity, underscores its effectiveness and adaptability. As machine learning continues to evolve, CatBoost remains a valuable tool for practitioners seeking to leverage advanced gradient boosting techniques in their predictive modeling efforts.

The CB classifier algorithm underwent grid search for the parameters depth and learning_rate. The depth parameter determines the depth of the trees used, while the learning_rate sets the learning rate for each iteration of the model. In this study, a depth value of 8 and a learning_rate value of 0.1 were selected for the CB algorithm. The classification results obtained using the CB algorithm are presented through the confusion matrix (Figure 8). The results indicate that the model achieved an accuracy of 86.80%, with a sensitivity value of 81.92%, a specificity value of 90.70%, and an F_1 score of 0.84.

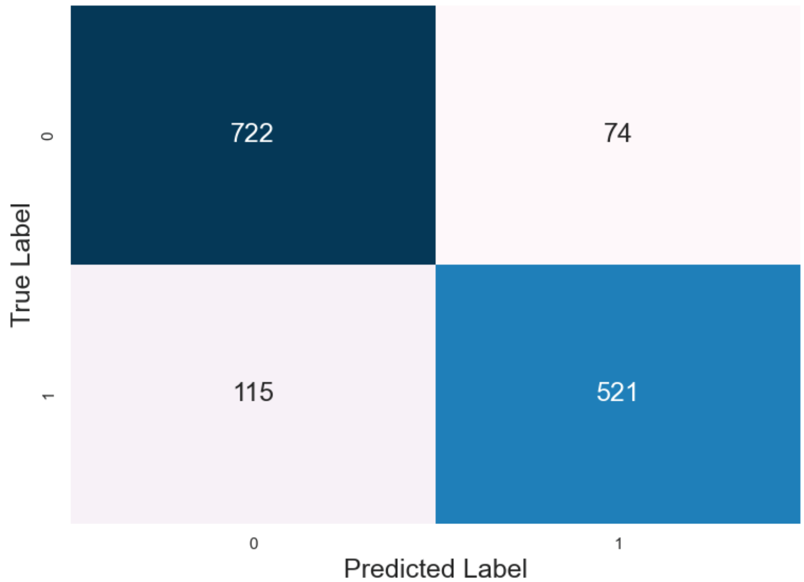

Figure 8. Confusion matrix obtained by CatBoost classifier.

To visualize the model's performance, the ROC curve is presented in Figure 9. The calculated ROC AUC value is determined to be 0.96. This high value emphasizes the model's strong discriminative power.

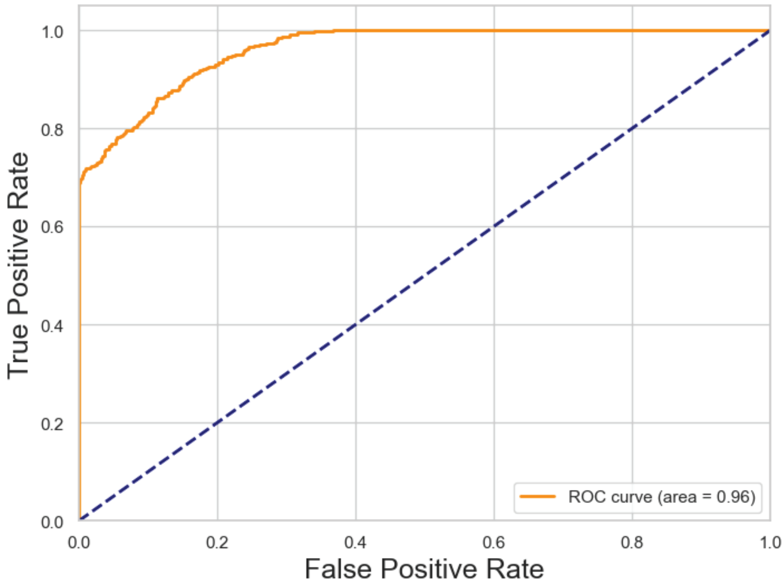

Figure 9. ROC curve obtained by CatBoost classifier.

Random Forest (RF)

The Random Forest (RF)classifier is an ensemble learning method that utilizes multiple decision trees to improve classification accuracy and control overfitting. Developed by Leo Breiman in 2001, this algorithm has gained widespread popularity due to its robustness, versatility, and ease of use across various domains, including ecology, finance, and healthcare (Chen et al., 2021; Cutler et al., 2007)

The RF algorithm operates by constructing a multitude of decision trees during training and outputting the mode of the classes (classification) or mean prediction (regression) of the individual trees. Each tree is built using a random subset of the training data, which is achieved through a technique known as bootstrap aggregating, or bagging. This method helps to reduce variance and improve the model's generalization capabilities (Feng et al., 2015; Shahhosseini & Hu, 2021). Additionally, at each split in the tree, a random subset of features is considered, which further enhances the diversity among the trees and mitigates the risk of overfitting (D. Liu et al., 2021).

The RF algorithm has several advantages over traditional algorithms. One of these is its ability to generally achieve high accuracy. Its structure allows it to capture complex patterns within the data. By averaging the results of multiple trees, RF is less prone to overfitting compared to individual decision trees. Additionally, RF can effectively handle missing data, making it suitable for real-world applications where data may be incomplete (Cutler et al., 2007; Feng et al., 2015; D. Liu et al., 2021). Despite these advantages, training a large number of trees can be computationally intensive, especially when dealing with high-dimensional data. The performance of the RF algorithm can be sensitive to hyperparameter settings, such as the number of trees and the maximum depth of each tree. Therefore, fine-tuning these parameters is essential for achieving optimal results. (Baita et al., 2023)

In conclusion, the RF classifier is a powerful and versatile tool in the machine learning arsenal. Its ability to handle complex datasets, provide insights into feature importance, and maintain high accuracy makes it suitable for a wide range of applications. As machine learning continues to evolve, RF remains a go-to method for practitioners seeking reliable and effective classification solutions.

Grid search has been applied to the RF algorithm for the parameters of *max_depth*, *min_samples_split*, and *n_estimators*. Among these parameters, *max_depth* determines the maximum depth of the trees, *min_samples_split* indicates the minimum number of samples required to split a node, and *n_estimators* specifies the number of trees to be used in the model. For this study, the number of *n_estimators* was set to 200, *max_depth* was set to "none," and *min_samples_split* was set to 10. With these settings, the model demonstrated a high accuracy rate of 87.29% on the test set. The sensitivity value, which reflects the model's ability to correctly identify the positive class, was recorded at 81.13%. This indicates the model's competence in recognizing instances of the positive class. Furthermore, the specificity rate was notably impressive at 92.21%, showcasing strong performance in accurately predicting the negative class. Additionally, the F_1 Score of 85.01 suggests that the model exhibits balanced performance, effectively maintaining a good balance between positive and negative classes. The results of the confusion matrix can be seen in Figure 10.

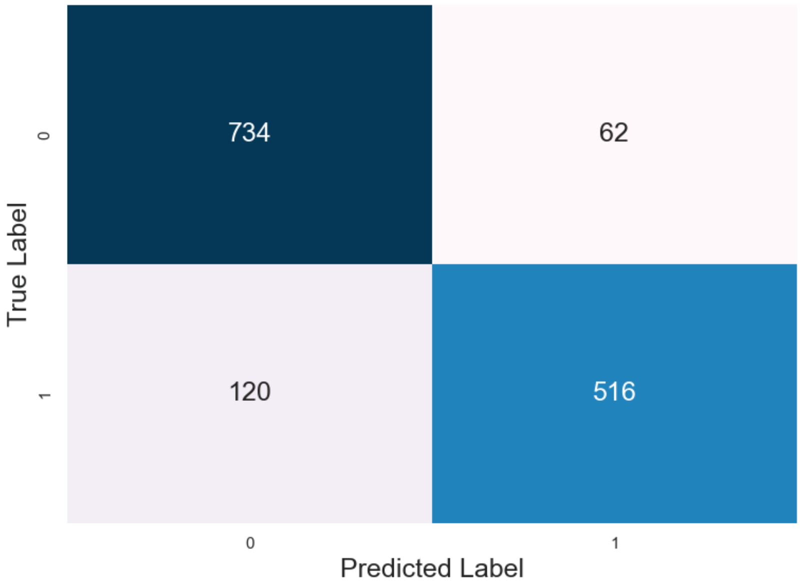

Figure 10. Confusion matrix resulting from the Random Forest method.

When visualizing the model's ROC curve, it can be observed that the curve approaches the top-left corner of the graph (Figure 11). This indicates a high discrimination performance of the model. Additionally, the ROC AUC value obtained for the study was found to be 0.96, further confirming the model's strong classification capability.

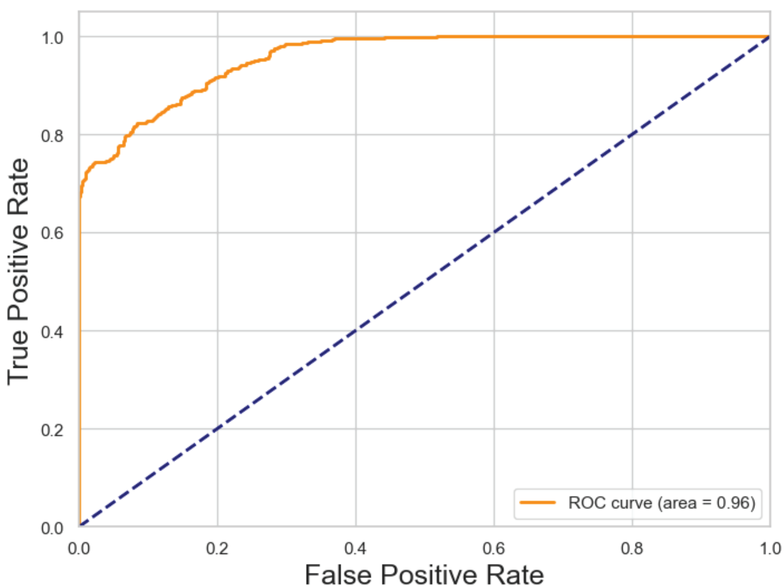

Figure 11. ROC curve resulting from the Random Forest method.

Support Vector Machine (SVM) Classifier

The Support Vector Machine (SVM) classifier is a powerful supervised learning algorithm primarily used for classification tasks. It is based on the concept of finding a hyperplane that best separates data points of different classes in a high-dimensional space. SVM is particularly effective in high-dimensional spaces and is well-suited for both linear and non-linear classification problems. SVM operates by transforming the input data into a higher-dimensional space using a kernel function, which allows it to find a hyperplane that maximizes the margin between different classes. The margin is defined as the distance between the hyperplane and the nearest data points from either class, known as support vectors. The objective of SVM is to maximize this margin, thereby enhancing the model's generalization capabilities (Cortes & Vapnik, 1995; Zhang et al., 2011).

SVM is widely used in image classification tasks, where it has shown superior performance compared to other classifiers. For example, it has been effectively utilized for facial expression recognition in real-time video streams (Michel & Kaliouby, 2003). In healthcare, SVM has been employed for diagnosing diseases, such as breast cancer, where it has demonstrated high accuracy in distinguishing between malignant and benign tumors. Its ability to handle high-dimensional data makes it particularly useful in medical imaging and genomics (N. Liu et al., 2018). SVM has been applied in pipeline security to classify signals and detect potential threats, showcasing its versatility in security applications (Tan et al., 2016)

SVM is effective in high-dimensional spaces and is robust to overfitting, especially when the number of dimensions exceeds the number of samples. The use of different kernel functions allows SVM to adapt to various types of data distributions, making it a flexible choice for many classification tasks (Zhang et al., 2011). By applying kernel tricks, SVM can efficiently handle non-linear classification problems, which are common in real-world datasets (Gurram & Kwon, 2010). Training SVM can be computationally intensive, especially for large datasets, as the algorithm's complexity increases with the number of training samples (Zhang et al., 2011). The performance of SVM is sensitive to the choice of kernel and its parameters, necessitating careful tuning to achieve optimal results (Huang & Wang, 2006; Manik et al., 2022).

In the application of the SVM algorithm, three parameters were utilized during grid search: C, kernel, and gamma. The C parameter is the regularization parameter, which controls the trade-off between achieving a low training error and a low testing error. The kernel specifies the type of kernel function used; a linear kernel provides a straightforward classification, while the radial basis function (RBF) kernel can separate data with more complex boundaries. Gamma defines the influence range of the kernel. In this study, the parameters were set as follows: C = 0.1, gamma = "scale," and kernel = "linear." According to the confusion matrix results (Figure 12), the classification performance of the model was assessed, revealing a total of 702 true negatives (correct negative predictions) and 507 true positives (correct positive predictions). However, there were also 94 false positives (Type I error) and 129 false negatives (Type II error). This indicates that the model's ability to correctly identify the positive class (diabetes) is relatively lower than that of other algorithms, with a sensitivity value of 79.72%. Additionally, the accuracy was found to be 84.43%, while the specificity reached 88.19%. The F_1 score was calculated to be 0.82.

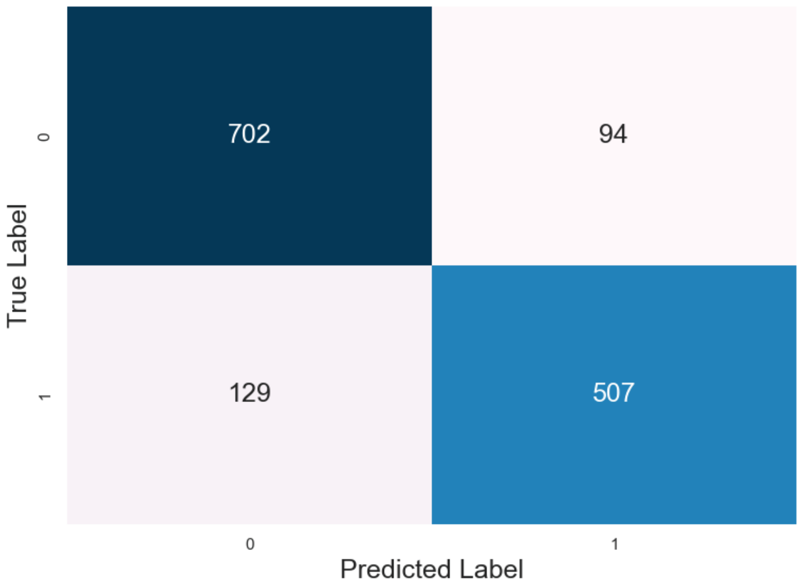

Figure 12. Confusion matrix of Support Vector Machine classifier.

The ROC AUC value of the model was recorded as 0.94. Although this value is high, it is essential to evaluate the model using all metrics in such applications. Consequently, the performance of the SVM classifier algorithm falls slightly behind that of other algorithms. The ROC curve is illustrated in Figure 13.

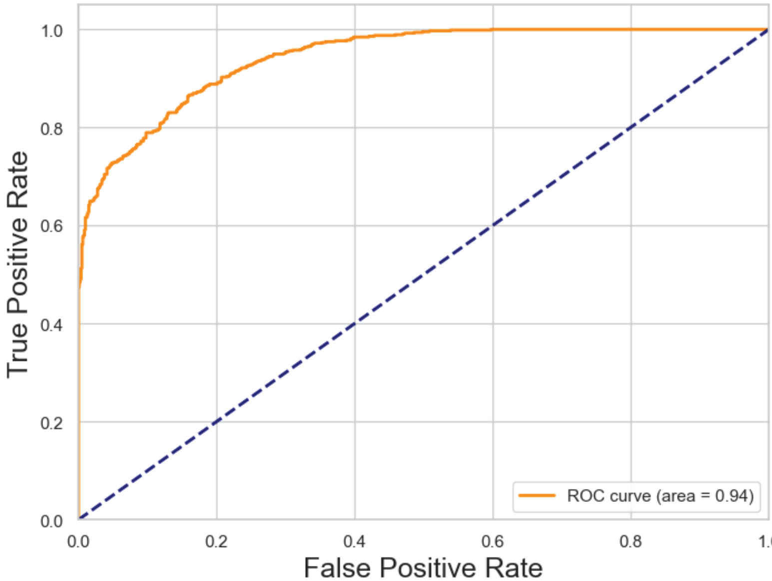

Figure 13. ROC curve of Support Vector Machine classifier.

Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) classifier is a type of artificial neural network that consists of multiple layers of neurons, including an input layer, one or more hidden layers, and an output layer. MLPs are widely used for supervised learning tasks, particularly for classification and regression problems. They are capable of modeling complex relationships in data due to their ability to learn non-linear mappings through the use of activation functions (Shimobaba et al., 2017; Wuzhao, 2024).

An MLP is composed of interconnected nodes (neurons) organized in layers. Each neuron in a layer receives input from the previous layer, applies a weighted sum, and then passes the result through a non-linear activation function, such as the sigmoid, hyperbolic tangent, or ReLU (Rectified Linear Unit) (Bodapati & Naralasetti, 2019). The output of the neurons in the final layer represents the predicted class probabilities for classification tasks. The training of an MLP involves adjusting the weights of the connections between neurons using a process called backpropagation, which minimizes the difference between the predicted outputs and the actual target values. This is typically done using optimization algorithms such as stochastic gradient descent (SGD) or Adam (Shi et al., 2020).

MLPs can approximate any continuous function due to their non-linear activation functions, making them suitable for complex datasets

(Shimobaba et al., 2017). The architecture of MLPs can be easily adjusted by varying the number of hidden layers and neurons, allowing for customization based on the specific problem (Bodapati & Naralasetti, 2019). MLPs can automatically learn relevant features from raw data, reducing the need for manual feature engineering (Shi et al., 2020). Despite these, MLP has some disadvantages. MLPs can easily overfit the training data, especially when the model is too complex relative to the amount of training data available. Techniques such as dropout, regularization, and early stopping are often employed to mitigate this issue (Kumar, 2024). Training MLPs can be computationally expensive and time-consuming, particularly for large datasets and deep architectures (Zhang et al., 2011). The performance of MLPs is highly dependent on the choice of hyperparameters, such as learning rate, number of layers, and number of neurons per layer. Careful tuning is required to achieve optimal results (Cabessa & Villa, 2014).

In conclusion, the MLP classifier is a powerful and versatile tool in the field of machine learning. Its ability to model complex relationships and learn from data makes it suitable for a wide range of applications, from image classification to financial forecasting. However, practitioners must be aware of the challenges associated with MLPs, including overfitting and computational demands, and apply appropriate techniques to address these issues. As machine learning continues to advance, MLPs remain a foundational method for many classification tasks.

In this study, the MLP algorithm underwent grid search for the parameters *hidden_layer_sizes*, *activation*, *solver*, *alpha*, and *max_iter*. The *hidden_layer_sizes* parameter determines the number of hidden layers and neurons within those layers. The activation parameter specifies the activation function used in the network, while the solver indicates the algorithm to be used for training the network. Alpha serves as a regularization parameter, and *max_iter* specifies the number of iterations for training the model.

For the MLP, the parameters were set as follows: *max_iter* at 1000, *activation* as "logistic," *alpha* as 0.001, *hidden_layer_sizes* as (50,), and *solver* as "adam". With this combination of parameters, the model achieved an accuracy of 84.29% on the test dataset. The model's sensitivity was determined to be 81.60%. Additionally, the specificity of the model was calculated as 86.43%. The F_1 score was found to be 82.19, and the confusion matrix for the model is presented in Figure 14. According to the results of the model using the MLP algorithm, the ROC AUC value was found to be 94.56%. The graph of the ROC curve is presented in Figure 15.

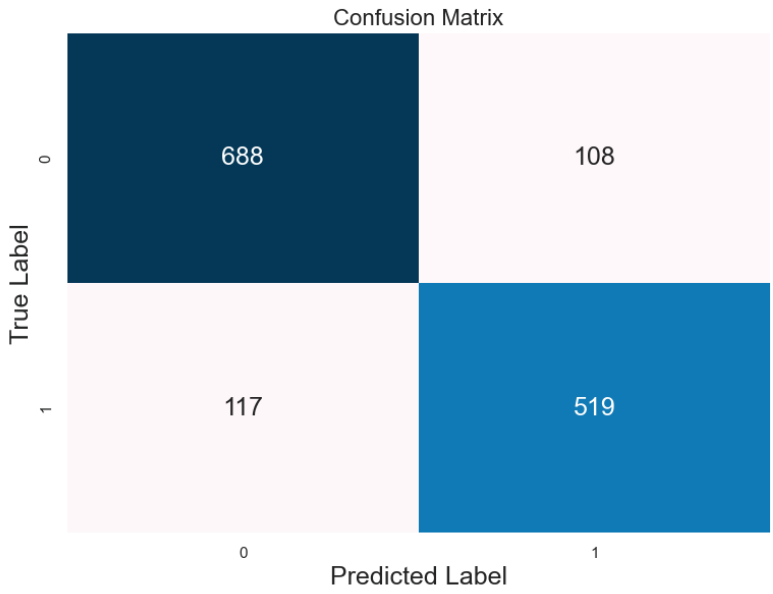

Figure 14. Confusion matrix obtained by Multilayer Perceptron.

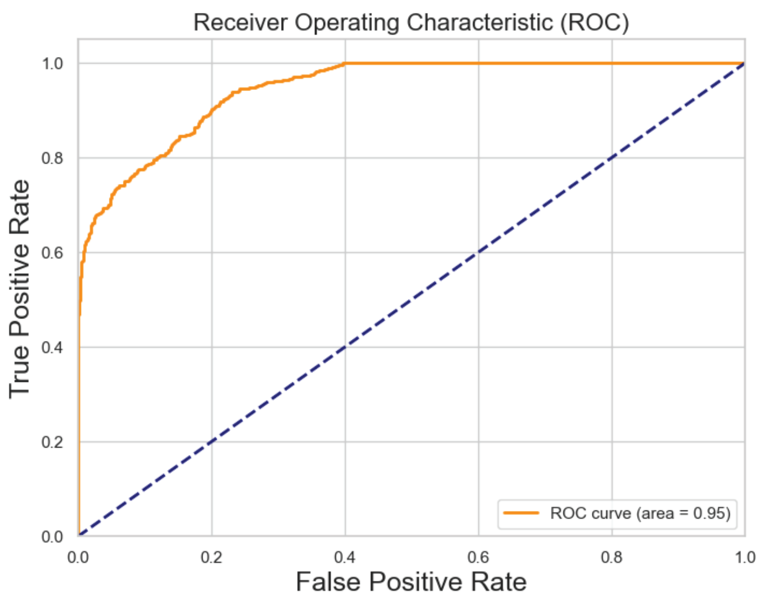

Figure 15. ROC curve obtained by Multilayer Perceptron.

Deep Neural Network (DNN)

Deep Neural Networks (DNNs) are a class of machine learning models that consist of multiple layers of interconnected nodes (neurons), enabling them to learn complex patterns in data. DNNs have gained significant attention in recent years due to their remarkable performance in various tasks, including image classification, natural language processing, and speech recognition (R. A. Li & Liu, 2020). A typical DNN consists of an input layer, one or more hidden layers, and an output layer. Each layer comprises multiple neurons, where each neuron applies a weighted sum of its inputs followed by a non-linear activation function, such as ReLU (Rectified Linear Unit) or sigmoid. The depth of the network (i.e., the number of hidden layers) allows DNNs to model intricate relationships in the data (Trier et al., 2018). The training process involves adjusting the weights of the connections between neurons using backpropagation, which minimizes the loss function that quantifies the difference between the predicted and actual outputs. Optimization algorithms, such as stochastic gradient descent (SGD) or Adam, are commonly used to update the weights during training (Pyrkov et al., 2018).

DNNs can learn hierarchical representations of data, allowing them to capture complex patterns that simpler models may miss. DNNs automatically learn relevant features from raw data, reducing the need for manual feature engineering, which is often a bottleneck in traditional machine learning approaches and can be scaled to handle large datasets and complex tasks, making them suitable for applications in big data environments (Pyrkov et al., 2018; Wuzhao, 2024).

DNNs are prone to overfitting, especially when the model is too complex relative to the amount of training data available. Techniques such as dropout, regularization, and early stopping are often employed to mitigate this issue. Training DNNs can be computationally intensive and time-consuming, requiring powerful hardware such as GPUs to accelerate the training process (Trier et al., 2018).

In summary, DNNs are a powerful and versatile tool in the field of machine learning, capable of modeling complex relationships and learning from large datasets. Their application across various domains, including medical imaging, speech recognition, and remote sensing, underscores their effectiveness and adaptability. However, practitioners must be aware of the challenges associated with DNNs, such as overfitting and computational demands, and apply appropriate techniques to address these issues. As machine learning continues to evolve, DNNs remain a foundational method for many classification tasks.

In this study, the Keras module was used to implement a DNN. Keras stands out among deep learning libraries for its ease of use and broad support. When creating the Keras model, an input layer with 64 neurons was chosen, with the activation function set to "relu." Subsequently, a hidden layer with 32 neurons and the "relu" activation function was added. A batch normalization layer was then included to normalize the data. To prevent overfitting, a dropout layer with a value of 0.4 was added. Following that, another hidden layer with 16 neurons and the "relu" activation function was utilized. Finally, an output layer with the "sigmoid" activation function was added. The "adam" optimizer was used for training. Given that the dataset is relatively small, a shallower network was preferred. The architectural diagram of the created network is shown in Figure 16.

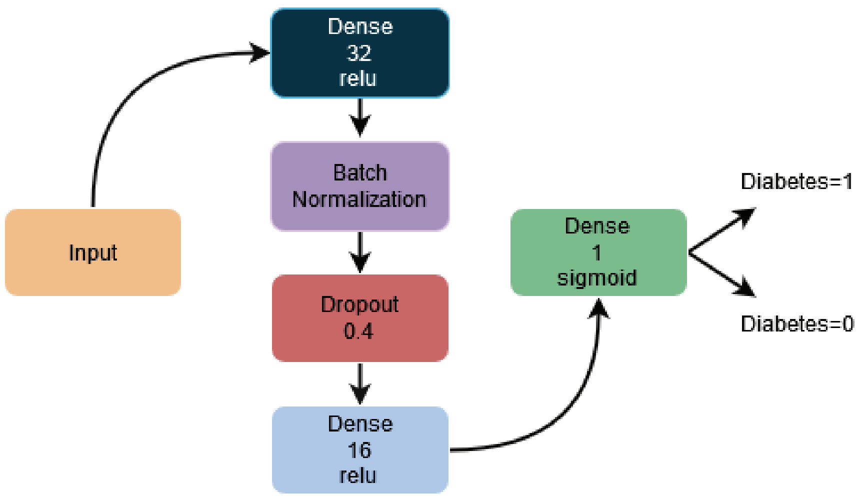

Figure 16. DNN architecture used in the study.

The model achieved an accuracy rate of 92.25% on the test data, indicating that it classified a significant portion of all examples in the test set correctly. The model's ability to effectively identify positive class (diabetes) examples was determined using the sensitivity (recall) metric. The obtained sensitivity rate of 90.28% demonstrates the model's high capability to accurately identify patients. This is critically important in the healthcare field, as overlooking the disease can delay treatment processes. The results are illustrated in the confusion matrix shown in Figure 17.

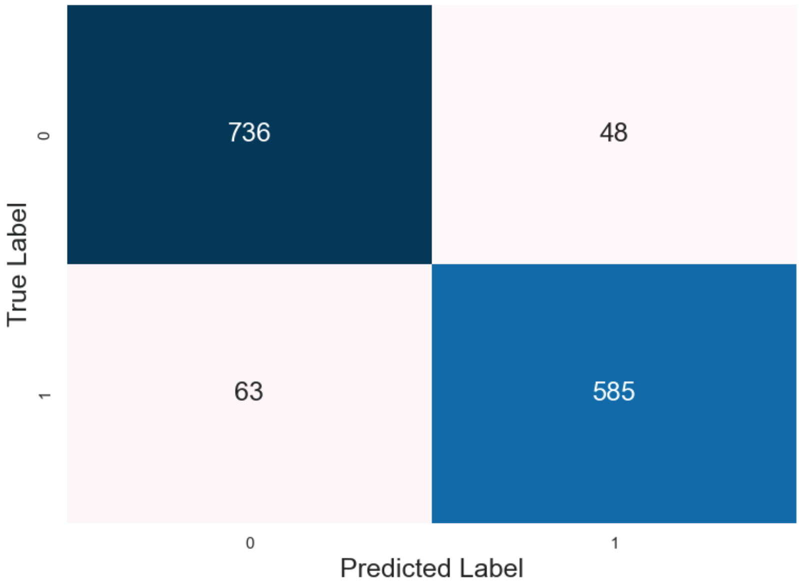

Figure 17. Confusion matrix of Deep Neural Network.

The model's specificity rate was calculated to be 93.88%, indicating its effectiveness in identifying healthy individuals. High specificity minimizes false positive results, thus preventing unnecessary anxiety and additional testing. To better reflect the overall success of the model, the F_1 score was determined to be 91.33%. The F1 score provides a balance between sensitivity and precision, reflecting the classification model's ability to effectively distinguish between both positive and negative class examples. Additionally, the ROC AUC value, which evaluates the model's discriminative power, was obtained at 0.97. This high value reinforces the model's success in distinguishing between positive and negative classes. The ROC curve is illustrated in Figure 18.

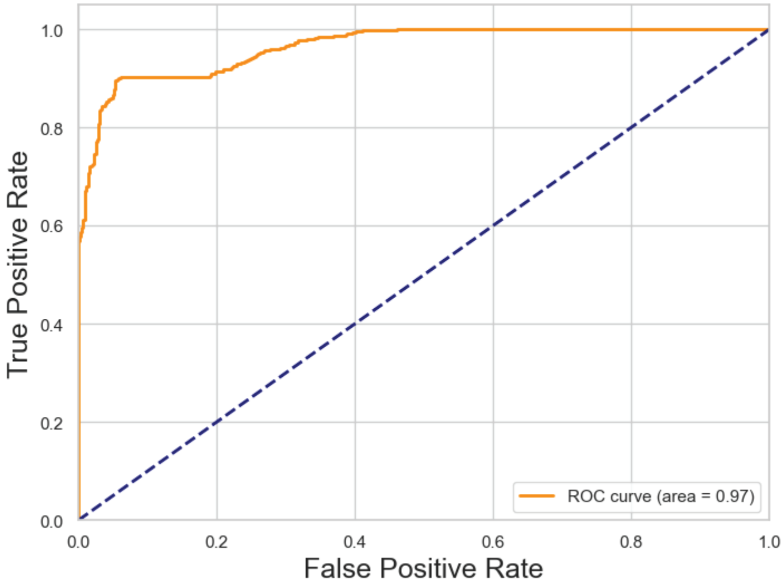

Figure 18. ROC curve of Deep Neural Network.

Web Based Prediction Interface

The best results were achieved with the model using the DNN approach, leading to the saving of the model weights. This allows the project's sub-goal of creating a web-based prediction system to send data and provide predictions to users. The developed web application features a backend built on the Python-based Flask framework, with a frontend constructed using JavaScript. This setup enables visitors to input their information and view the model's predictions regarding their diabetes status. A screenshot of the developed interface is shown in Figure 19.

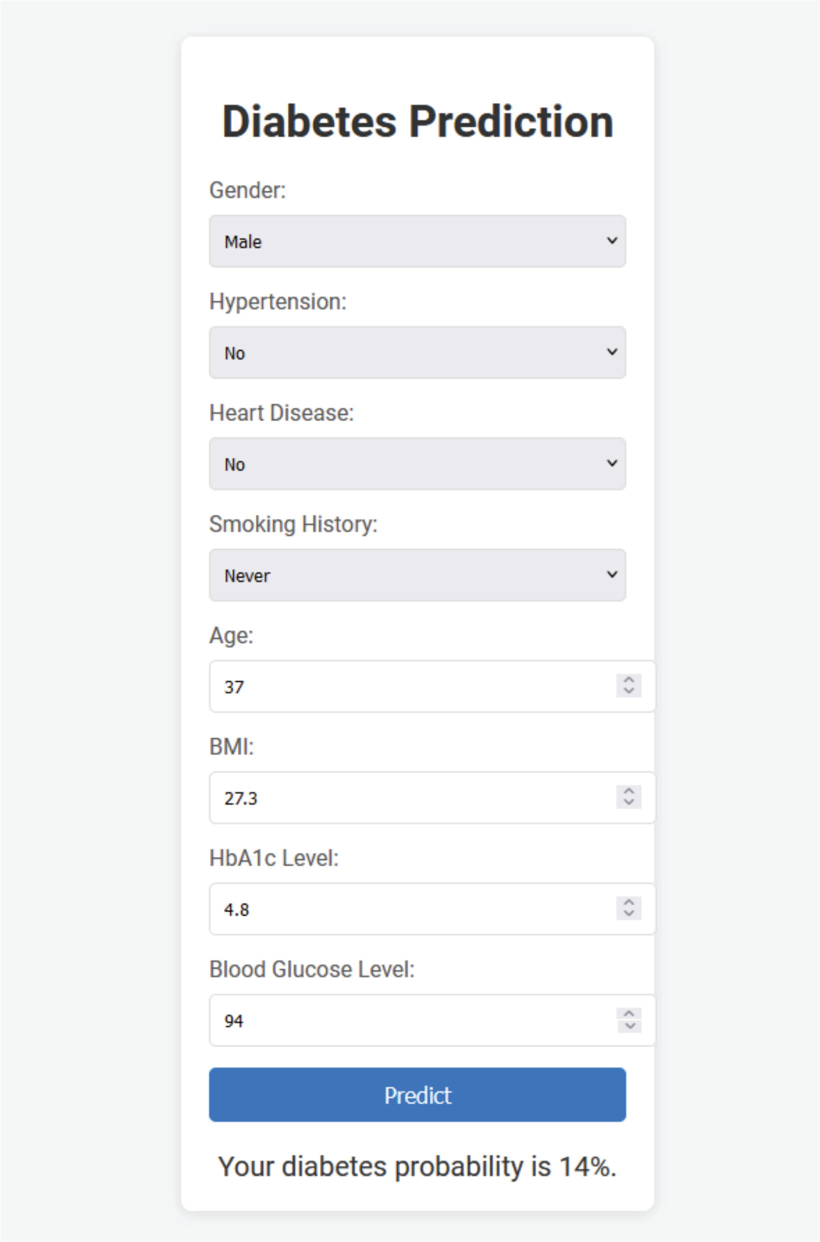

Figure 19. Web interface where end user can make predictions.

CONCLUSION

This study aimed to develop a comprehensive machine learning-based system for predicting the risk of diabetes mellitus by analyzing routine laboratory blood tests and daily lifestyle habits. By comparing the performance of multiple machine learning algorithms, including K-Nearest Neighbors (KNN), Logistic Regression (LR), CatBoost (CB), Random Forest (RF), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Deep Neural Networks (DNN), the study demonstrated the efficacy of these methods in handling a complex, imbalanced dataset. The results offer valuable insights into the advantages and limitations of each algorithm in the context of diabetes risk prediction, contributing to a growing body of research on the application of artificial intelligence in healthcare.

The study revealed that the Deep Neural Network (DNN) model achieved the best overall performance, with an impressive accuracy of 92.25%, sensitivity of 90.28%, specificity of 93.88%, and an F_1 score of 0.91. The DNN also registered the highest ROC AUC score of 0.97, indicating excellent discriminatory power between diabetic and non-diabetic cases. The ability of DNN to handle complex, nonlinear relationships between variables likely contributed to its superior performance in predicting diabetes. Furthermore, its architecture, which includes multiple hidden layers and optimized activation functions, allows it to capture intricate patterns in the dataset that simpler models might miss.

In contrast, the K-Nearest Neighbors (KNN) algorithm performed the worst among the models tested, with an accuracy of 81.70% and a sensitivity of 76.42%. Although KNN is a well-established and intuitive algorithm, its performance was limited in this application due to the high-dimensional nature of the dataset and the imbalanced distribution of the target variable (diabetes status). The results suggest that KNN may not be the most appropriate model for predicting diabetes risk in datasets that require the algorithm to distinguish subtle patterns between classes.

Other models, such as Logistic Regression (LR), CatBoost Classifier (CBC), Random Forest (RF), and Support Vector Machine (SVM), performed moderately well, with accuracies ranging between 84.29% and 87.29%, and F_1 scores between 0.82 and 0.85. While these models provided reliable predictions, they were slightly outperformed by the DNN, particularly in terms of sensitivity and ROC AUC values. The Random Forest and CatBoost classifiers, both ensemble methods, exhibited particularly strong performance, reflecting their ability to handle feature interactions and mitigate overfitting. These algorithms consistently balanced high specificity with moderate sensitivity, making them useful for scenarios where reducing false positives is critical. Metric results for all models used are presented in Table 1.

Table 1. Metric results of algorithms.

Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)	F_1 Score	ROC AUC
KNN	81.70	76.42	85.93	0.79	0.91
Logistic Regression	84.85	80.19	88.57	0.82	0.94
CatBoost Classifier	86.80	81.92	90.70	0.84	0.96
Random Forest	87.29	81.13	92.21	0.85	0.96
SVM	84.43	79.72	88.19	0.82	0.94
Multilayer Perceptron	84.29	81.60	86.43	0.82	0.94
Deep Neural Network	**92.25**	**90.28**	**93.88**	**0.91**	**0.97**

One of the key challenges in this study was addressing the imbalanced nature of the dataset, where the majority of cases were non-diabetic. To handle this, undersampling techniques were applied, particularly to ensure a more balanced distribution of the target variable, leading to improved classification performance across all models. This technique is especially important in healthcare-related machine learning tasks, where misclassification can have serious consequences. Failing to detect diabetes, for example, could delay crucial medical interventions.

The importance of evaluating machine learning models using multiple performance metrics cannot be overstated, particularly in the context of medical diagnoses. While accuracy is a commonly used metric, it alone does not provide a complete picture in the case of imbalanced datasets. In this study, sensitivity (the ability to correctly identify diabetic cases) and specificity (the ability to correctly identify non-diabetic cases) were equally important. High sensitivity ensures that most true diabetic cases are correctly identified, which is critical in healthcare, where missing a diagnosis can lead to severe complications. On the other hand, high specificity reduces false positives, thereby minimizing unnecessary interventions and anxiety for patients.

The integration of machine learning into diabetes risk prediction has the potential to transform traditional screening methods. The DNN model developed in this study was implemented in a web-based interface, enabling individuals to input personal health data and receive a prediction of their diabetes risk. This application has far-reaching implications for preventive healthcare. By facilitating early detection of diabetes, it enables patients to take proactive steps to manage their health, potentially reducing the burden of diabetes-related complications such as cardiovascular disease, kidney failure, and neuropathy.

Furthermore, the success of this study underscores the need for interdisciplinary collaboration between healthcare professionals and data scientists. Developing accurate predictive models for medical conditions like diabetes requires not only sophisticated algorithms but also a deep understanding of the disease and its contributing factors. Machine learning can process large amounts of data more efficiently than traditional statistical methods, identifying patterns and correlations that may not be immediately apparent. This capability is particularly valuable for managing chronic diseases like diabetes, where early diagnosis and personalized treatment plans can lead to significantly improved outcomes.

Finally, while the web-based prediction interface developed in this study is a significant step towards democratizing access to diabetes risk assessment, its impact could be further amplified through integration with existing healthcare systems. For instance, clinicians could use the tool to assist with early diagnosis during routine check-ups, or it could be deployed as part of a larger public health initiative aimed at reducing the prevalence of undiagnosed diabetes. By combining machine learning technology with preventive healthcare strategies, we can make significant strides in combating the global diabetes epidemic.

Looking ahead, there are several avenues for further research and development. While the DNN model demonstrated the best performance, there is always room for improvement. Additionally, further refinements to the model's architecture, such as experimenting with deeper networks or more advanced regularization techniques, may enhance its predictive power. Future studies could focus on enhancing the model by integrating additional features, such as genetic data, lifestyle behaviors, and environmental factors, which are known to play significant roles in diabetes risk. Expanding the dataset to include more diverse populations across various demographic and geographic backgrounds would also improve the generalizability and robustness of the predictions. Hybrid approaches, combining the strengths of different machine learning algorithms, could yield better performance, particularly when addressing the complexities of imbalanced datasets.

In conclusion, this study has demonstrated that machine learning, particularly Deep Neural Networks, offers a powerful tool for predicting diabetes risk. The developed web-based interface provides an accessible platform for individuals to assess their own risk, offering an opportunity for early intervention. As healthcare continues to embrace digital transformation, the integration of machine learning into diagnostic and predictive models will play a crucial role in enhancing patient care and improving public health outcomes.

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USING ARTIFICIAL INTELLIGENCE-ENHANCED VIRTUAL REALITY AND IMAGE PROCESSING FOR SPECIAL EDUCATION: A PROPOSAL FOR TÜRKIYE

This part explores the implementation of virtual reality (VR) and image processing technologies within the context of special education in Türkiye. Special education, a critical but often under-resourced area, has seen significant advancements through the integration of these technologies. By focusing on cognitive and self-care skill development, this study showcases how modern technological solutions can be adapted to meet the unique needs of students with intellectual disabilities and autism spectrum disorders. The chapter discusses the technological infrastructure, educational strategies, and the impact on student learning outcomes, offering valuable insights into how emerging technologies can transform special education practices, particularly in regions with limited resources.

INTRODUCTION

Special education is a field that includes educational programs and practices designed to meet the specific needs of individuals. According to the Special Education Services Regulation, special education is the education provided in appropriate settings with specially trained personnel and developed to meet the educational and social needs of individuals who show significant differences from their peers in terms of individual and developmental characteristics as well as educational competencies. (Özel Eğitim Hizmetleri Yönetmeliği, 2018). In special education practices, the preparation and implementation of Individualized Education Programs (IEP) hold critical importance. The IEP is a plan designed to meet the educational needs of individuals with special needs, and its effective implementation supports the academic and social development of students (Kumcağız et al., 2017; E. Yılmaz & Batu, 2016). Practices in this field are influenced by various factors such as the qualifications of teachers, inclusive education, guidance services, and individualized education programs. To achieve success in the education of individuals with special needs, it is essential to consider and continuously improve these factors.

The social and self-care issues of individuals with special education needs negatively affect their educational processes and quality of life. These individuals' social skills are often more limited compared to their peers, which is due to their weak communication skills (Akyürek & Sipahi, 2022). The development of social skills is one of the main objectives of special education programs, and these programs aim to enable individuals to be more effective in social environments (Açar et al., 2022). Additionally, self-care skills are of critical importance in enhancing the independence of these individuals (Dinçer et al., 2017). Particularly in preschool education, the challenges that children with special needs face in adapting to school and developing self-care skills stem from the education system not being sufficiently supportive for these individuals (Özdoğru, 2021). Deficiencies in education can negatively impact the development of social skills, which in turn can increase the challenges individuals face in social life (Acar et al., 2023). Additionally, challenges in implementing IEPs in the education of individuals with special needs lead to their needs not being adequately met (Aktaş & Argün, 2021; Tekin Ersan & Ata, 2017).

The historical development of special education services in Turkey dates back to the Ottoman period, and the practices in this field have been diversifying over time (İmamoğlu, 2022). Throughout the history of the Republic, regulations, laws, development plans, government programs, special education-related committees, and the activities of official/private institutions, as well as efforts to train personnel, have played a significant role in ensuring that individuals with special needs gain educational, economic, social, and cultural rights (Çitil, 2017). Special education in Turkey, while a relatively small field within the general education system, has been gaining attention as it grows. According to official data, while the total number of formal education institutions increased by 22% from the 2012-2013 to the 2022-2023 academic year, the increase in special education institutions was 47%. Similarly, over these 10 years, the total number of students in formal education grew by 15%, whereas the number of students in special education saw a remarkable 130% increase. As of the 2022-2023 academic year, special education institutions make up approximately 2.48% of all educational institutions, while special education students account for 2.55% of the total student population (Milli Eğitim Bakanlığı, 2023). The fact that male students participate in special education at a higher rate (63%) compared to females highlights an inequality in the field. This suggests that access to special education services may be more limited in rural and disadvantaged areas. The limited infrastructure and gender disparity in special education in Turkey indicate areas where improvements in equality and access to education are needed.

The integration of technology in the education of students with special needs has become increasingly important. Assistive technologies such as mobile applications and augmented reality are designed to enhance the learning experiences of these students and increase accessibility (Hamutoğlu et al., 2022; Istiyati et al., 2023; Yıldız et al., 2022). These technologies not only facilitate communication and participation but also promote inclusivity in educational environments (Istiyati et al., 2023; Iyamuremye et al., 2023). However, obstacles such as insufficient infrastructure and a lack of teacher training can hinder the effective use of technology in special education (Çağıltay et al., 2019; Y. Yılmaz et al., 2021).

Additionally, the successful implementation of technology requires a careful assessment of individual student needs and the selection of appropriate assistive tools to address those needs (Maebara et al., 2022). Research shows that when teachers are equipped with the necessary knowledge and skills regarding assistive technologies, the educational outcomes for students with special needs improve significantly (Surajudeen et al., 2022). Therefore, continuous professional development and access to resources are essential to maximize the benefits of technology in special education (Bağlama et al., 2022; Xia et al., 2023).

The use of virtual reality (VR) and image processing technologies in special education offers significant opportunities to enrich learning processes and contribute to the education of students with special needs (Özdemir et al., 2019). Virtual reality (VR) is defined as a computer-generated simulation that immerses users in a three-dimensional environment, allowing them to interact as if they were physically present in that environment (Lin, 2022; Zaharuddin et al., 2021). Recent developments in VR technology have significantly increased its accessibility and applicability in various fields, particularly in healthcare, education, and entertainment sectors (Al Farsi et al., 2021; Kumar, 2024). VR applications enable students to concretize abstract concepts and experience real-world scenarios, while also helping to develop social skills. For instance, VR applications designed for individuals with autism spectrum disorder offer simulations aimed at improving social interaction skills, allowing these students to engage more comfortably and effectively in social environments (Kahveci & Sondaş, 2023; Özdemir et al., 2019).

Image processing technologies enable the development of customized solutions tailored to the needs of individuals in special education. These technologies can be used to monitor and assess students' learning processes, allowing teachers to intervene with strategies suited to individual needs (Kutlu et al., 2018; Yildiz & Yikmiş, 2020). Additionally, applications supported by image processing can enhance students' attention and focus, making the learning process more effective (Çay et al., 2020).

This study aims to develop an environment that utilizes simultaneous image processing and virtual reality technologies to contribute to the development of cognitive and self-care skills for individuals with special education needs.

MATERIAL AND METHODOLOGY

Target Audience

In educational institutions affiliated with the Ministry of National Education, individuals requiring special education are present at preschool, primary, secondary, and high school levels. According to the summary tables for the 2022-2023 academic year, there are approximately 507,000 students registered across all these levels (Milli Eğitim Bakanlığı, 2023). This study specifically targets primary and secondary school students with mild, moderate, or severe intellectual disabilities or autism spectrum disorder. These students may receive education in various institutions and classrooms. Special education classes are designed for students with visual, hearing, intellectual disabilities, or autism, and are organized based on the type and degree of disability. Inclusive education, on the other hand, provides support services for students with special education needs, enabling them to continue their education alongside students without disabilities. Specifically, there are primary and secondary schools for students with mild intellectual disabilities, while special education practice schools are available for students with moderate to severe intellectual disabilities or autism spectrum disorder.

According to the 2022-2023 data, approximately 61,000 students are enrolled in special education classes at the primary and secondary school levels, while around 310,000 students are receiving inclusive education. However, no specific numerical data has been provided regarding the proportion of students with mild, moderate, or severe intellectual disabilities or autism spectrum disorder among these students. Figure 1 shows the distribution of 25,548 students receiving education in schools for students with mild intellectual disabilities and special education practice schools. The activities developed were selected according to this level.

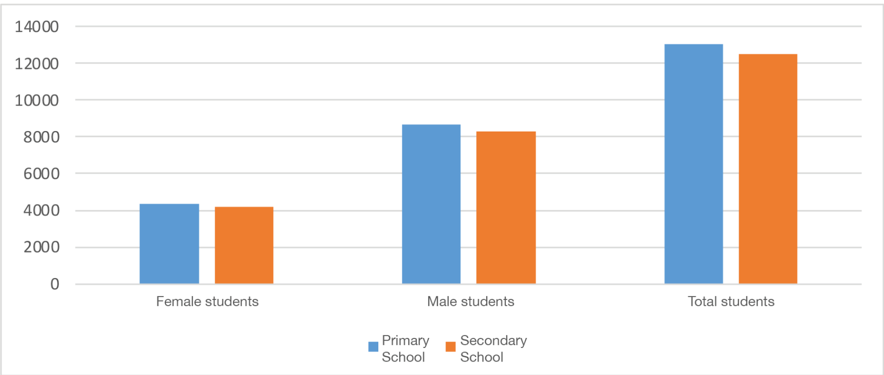

Figure 1. The number of students in primary and secondary schools for individuals with mild intellectual disabilities, as well as in special education practice schools (Level I and Level II).

Content of the Application

During the creation of the content for the application, the "Performance Assessment Form for Individuals with Intellectual Disabilities" published by the General Directorate of Special Education Guidance and Counseling Services was used as a reference. According to this form, an educational plan needs to be developed for individuals requiring special education and those with intellectual disabilities, covering areas such as cognitive skill preparation, self-care skills, daily living skills, social life skills, speech and alternative communication skills, psychomotor skills, social life, Turkish language, and mathematics skills. In this study, modules focusing on cognitive skills and self-care skills were developed.

Platforms Used

During the development of the application, the Unity game engine and C# programming language were used. Unity is a cross-platform game engine used to develop video games and simulations for computers, consoles, and mobile devices [33]. Visual Studio 2022 was chosen for compiling the C# code during programming. The development process was carried out on a Windows-based computer equipped with an Intel i7 processor and 64 GB of memory.

Image Recognition

One of the critical stages of the application developed within the scope of this study is the detection of body limbs—such as the head, arms, and torso—using the image captured by the camera. To perform this task, MediaPipe, was used.

MediaPipe is an open-source framework developed by Google that facilitates the deployment of machine learning and computer vision solutions, particularly for real-time applications. It provides a versatile pipeline for various tasks, including human pose estimation, face detection, and hand tracking, making it a valuable tool in the fields of augmented reality (AR) and virtual reality (VR) (Lugaresi et al., 2019). The framework's modular design allows developers to create custom solutions tailored to specific needs, enhancing its applicability across different domains (Chung et al., 2022; Lugaresi et al., 2019).

In the context of face detection, MediaPipe employs advanced algorithms to identify facial landmarks, enabling applications such as emotion recognition, facial expression analysis, and user interaction in VR environments (Reddy, 2024; Zhang, 2020). The framework's capability to detect 3D coordinates of facial features allows for more immersive experiences in virtual settings, where user engagement is often enhanced by accurate facial tracking (Reddy, 2024). This is particularly relevant in VR applications where user avatars need to reflect real-time facial expressions to create a more authentic interaction experience.

MediaPipe Pose, a component of the MediaPipe framework, specializes in human pose estimation, providing real-time tracking of body movements through keypoint detection (Latyshev, 2024; Singh et al., 2022). This technology has been utilized in various applications, including fitness tracking, rehabilitation, and even dance rating systems, where precise body posture analysis is crucial (Ding, 2023; Parashar, 2023). The pose detection capabilities of MediaPipe are particularly beneficial in VR, where accurate body tracking is essential for creating realistic interactions and feedback within virtual environments (Jaiswal, 2023; Kwon & Kim, 2022). For instance, in fitness applications, MediaPipe can analyze a user's posture during exercises, offering real-time corrections to improve technique and prevent injuries (Jaiswal, 2023).

The relationship between MediaPipe's face and pose detection capabilities is significant in the context of VR applications. By integrating both face and body tracking, developers can create comprehensive systems that monitor user movements and expressions simultaneously, enhancing the realism and interactivity of virtual experiences (Mohd, 2023; Zhang, 2020). This dual capability allows for more sophisticated user interfaces in VR, where both body language and facial expressions can be interpreted to create responsive environments that adapt to user behavior (Mohd, 2023).

In summary, MediaPipe serves as a powerful tool for implementing face and pose detection in virtual reality applications. Its ability to provide real-time tracking of both facial and body movements enables developers to create immersive experiences that respond to user interactions, thereby enhancing engagement and realism in virtual environments (Latyshev, 2024; Lugaresi et al., 2019; Zhang, 2020). The integration of these technologies not only improves user experience but also opens up new possibilities for applications in gaming, training simulations, and social interactions within virtual spaces.

The developed application processes the video feed from the camera in real-time using the MediaPipe framework. Both the user's face and upper body are continuously analyzed in real-time. Landmarks are generated on the user's body and face, and actions are performed based on the coordinates of these landmarks. The facial and body landmarks utilized in the application are presented in Figure 2. This allows the user to maintain eye contact with the virtual avatar during interactions and to give commands using hand gestures. For the application to function stably, the user's hands must remain within the camera's field of view. To achieve this, it is sufficient for the individual to be approximately 100-150 cm away from the camera. A standard internal or external camera is adequate for capturing the images.

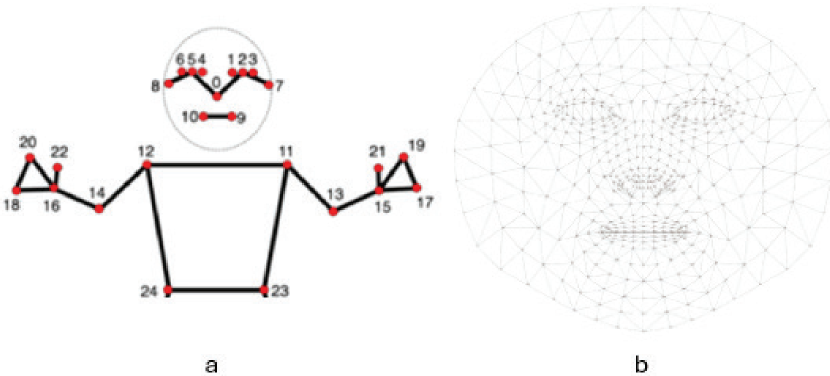

Figure 2. Pose landmarks used in the application (a) (Bang & Park, 2024), face landmarks used in the application (b) (Albadawi et al., 2023).

APPLICATION AND FEATURES

Virtual Assistant

When the application is first launched, a virtual assistant appears in front of the individual. The individual selects either a male or female virtual assistant to begin using the application, and they interact with this assistant throughout the experience (Figure 3). The individual raises the arm on the side of the assistant they wish to choose, thereby selecting their virtual assistant. The virtual assistant has the ability to communicate using gestures and facial expressions. Based on predefined scenarios, it can deliver necessary voiceovers and convey emotions. Simultaneous image processing techniques continuously monitor whether the individual is looking at the screen, and if not, the virtual assistant prompts them with a verbal reminder to look at the screen. Once the individual is ready, they can start interactive learning on a topic predetermined by their teacher, guardian, or themselves.

Figure 3. Virtual assistant selection screen.

Cognitive Skills Module

The cognitive skills module developed for individuals with intellectual disabilities focuses on supporting their mental processes such as thinking, problem perception, attention, memory, and learning. Cognitive skills encompass individuals' abilities to perceive information from their environment, process and interpret it, and respond appropriately. The goal of this program is to help individuals with intellectual disabilities acquire the ability to perceive, organize, analyze, and apply information functionally in daily life.

In the learning process, cognitive skills are addressed at a pace appropriate to the individual's mental capacity, following a structured approach. Each skill is developed step by step as part of a whole. Skills like problem-solving and attention management are taught in a complementary manner to help students make more independent and effective decisions in daily life.

The module is customized by teachers to suit the individual needs of each learner, aiming to maximize their cognitive development. It includes tasks such as simple math operations, distinguishing colors and shapes, matching items based on color or shape, identifying objects when named, and matching sounds with corresponding visuals. Figure 4 shows a screenshot taken during a lesson on teaching colors and shapes.

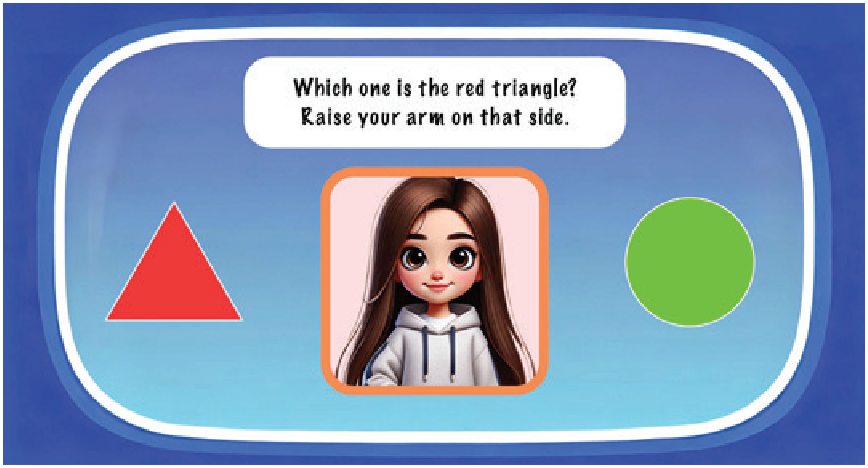

Figure 4. Cognitive skills module screen.

Self-Care Skills Module

The Self-Care Skills Module, designed to contribute to individuals' ability to live independently, aims to equip individuals with the self-care skills they can functionally use in daily life. It also helps them acquire the knowledge, skills, and behaviors needed to understand themselves, their environment, and the world around them. The knowledge, skills, and behaviors within the learning areas of the module are interconnected and presented in a holistic approach. Additionally, the knowledge, skills, and behaviors acquired in each learning area interact and support one another throughout the learning process.

In this module, the virtual assistant asks the individual questions related to daily life, and the individual is expected to provide the correct answer (Figure 5).

Figure 5. Self-care skills module screen.

These questions can include examples such as: "What should we do when we come home from outside?", "When should we brush our teeth?", "What should we do after leaving the bathroom?". The questions and options are presented both in written and spoken form. The individual can repeat the question as many times as needed and, when ready to answer, raises the hand on the side of the correct answer. The application continuously processes the image from the camera, analyzing which hand the individual raises without delay. Based on whether the answer is correct or incorrect, the individual is directed to a feedback screen.

Constructive Feedbacks

Constructive feedback plays a crucial role in the education of individuals with special needs because it directly impacts their learning outcomes and social development. Research shows that individuals with disabilities significantly benefit from concrete and direct feedback, which should be provided as close to the target behavior as possible (Whitby et al., 2012). This immediate reinforcement helps clarify expectations and encourages positive behaviors, making it easier for these students to understand and apply new concepts. Moreover, constructive feedback fosters a supportive learning environment where students feel valued and understood, which is essential for their emotional and psychological well-being. The impact of constructive feedback goes beyond academic performance; it also plays a critical role in building self-confidence and motivation. When individuals receive positive reinforcement for their efforts, they are more likely to actively engage in the learning process and develop a growth mindset. This is particularly important for students with special needs, who may face challenges with self-efficacy and motivation due to learning differences. In the developed application, constructive feedback is always provided to the student, whether the response is correct or incorrect. Additionally, this feedback is enhanced with visuals, sounds, and animations to ensure that the student's attention remains focused on the activity. An example feedback screen is shown in Figure 6a and 6b.

Figure 6a. Feedback screen for correct answer.

Figure 6b. Feedback screen for incorrect answer.

CONCLUSION

This study demonstrates the potential of integrating artificial intelligence, virtual reality (VR) and image processing technologies in special education to enhance cognitive and self-care skills development in students with special needs. By utilizing real-time tracking through MediaPipe's advanced pose and facial detection capabilities, the application developed offers an interactive and immersive learning environment tailored to the unique needs of each student. The integration of a virtual assistant not only supports individualized learning but also promotes engagement by providing continuous feedback based on user interaction, facilitating a more adaptive and responsive educational experience.

The modules designed for cognitive and self-care skills reflect the importance of addressing foundational skills for individuals with intellectual disabilities, helping them to navigate daily life with greater independence. The ability to customize these modules further empowers educators to meet the diverse requirements of each learner, ensuring that learning objectives align with the student's developmental stage. Additionally, the constructive feedback mechanism incorporated into the system plays a vital role in reinforcing positive behaviors and fostering both academic and social development in students.

This study aligns with the broader trends in assistive technology, where VR and image processing serve as transformative tools in making education more accessible and effective for individuals with special needs. However, to maximize the potential of such technologies, continued investments in infrastructure, teacher training, and the development of robust, inclusive systems are essential. As this field progresses, further research is needed to explore the long-term impact of such technologies on learners' academic outcomes and quality of life. The insights gained from this study offer promising directions for future innovations in special education and contribute to the growing body of knowledge on the application of AI-driven technologies in health and education.

Future studies could focus on adapting this application to different disability groups and testing them with various modules to make education more inclusive and accessible.

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AFTERWORD

As we reflect on the contents of this book, it becomes clear that we are standing on the cusp of a healthcare innovation. The blending of artificial intelligence, gamification, and personalized healthcare solutions marks a fundamental shift in how we approach patient care and disease prevention. The work presented here not only highlights current breakthroughs but also points toward an exciting future where healthcare is both preventative and engaging, driven by cutting-edge technology and innovation.

In the realm of physiotherapy, the development of gamified platforms like Therapinno represents a significant leap forward in making rehabilitation more accessible, engaging, and effective. Traditionally, physiotherapy is seen as a chore by many patients, leading to low adherence rates and less-than-optimal recovery outcomes. However, by embedding game-like elements into the rehabilitation process, patients are not only more likely to complete their prescribed exercises but also to do so with enthusiasm and commitment. AI's role in analyzing and adjusting patient movements in real-time ensures that exercises are performed accurately, helping patients avoid reinjury and recover more effectively. This technology could extend well beyond the physical rehabilitation space, finding applications in everything from athletic training to ergonomic workplace interventions, significantly improving health and well-being across diverse populations.

The diabetes risk assessment tool featured in this book is another instance in personalized healthcare. Chronic diseases like diabetes often develop silently, with symptoms appearing long after the condition has set in. The application of AI in predicting these risks, based on individual data inputs, brings a new level of precision and early intervention into healthcare. This approach allows individuals to take control of their health, making informed decisions that could delay or even prevent the onset of conditions like diabetes. As AI continues to evolve, we can envision more comprehensive systems that not only predict disease risk but offer personalized lifestyle and treatment recommendations, ensuring that each patient receives tailored care suited to their unique needs and circumstances.

The third study in this book explores the use of virtual reality and image processing technologies to support students with special needs, focusing on improving cognitive and self-care skills. By developing modules that utilize AI-driven tools for real-time tracking of body movements and facial detection, the study presents a highly adaptive and personalized learning environment. These VR-based systems provide continuous feedback, fostering engagement and individual progress. This technology not only empowers students with intellectual disabilities to acquire essential daily life skills but also shows the broader potential of AI and VR in making education and healthcare more inclusive and tailored to the specific needs of each individual. This opens up new opportunities for enhancing the quality of life and independence for students with varying levels of disabilities, providing a glimpse into the future of assistive education.

In conclusion, the studies in this book underscore the immense potential of AI-driven healthcare solutions to enhance patient engagement, improve outcomes, and promote a more personalized and proactive approach to health. The future of healthcare lies in leveraging these technologies to not only treat illness but to foster overall well-being. With continued research, development, and cross-disciplinary collaboration, we are poised to enter a new era of healthcare—one where artificial intelligence and human insight work hand in hand to create better health outcomes for all.

This is only the beginning of a much larger conversation about the role of technology in healthcare. We hope this book has inspired you to think more deeply about the possibilities that lie ahead and the ways in which we can harness the power of AI to improve lives on a global scale. The healthcare of tomorrow is one where patients are empowered, motivated, and fully engaged in their own care—and that is a future worth striving for.

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