The Prediction of Dry Weight for Chronic Hemodialysis Athletes Using a Machine Learning Approach: Sports Health Implications

Jae-Young Kim[1], Ji-Hye Kim[2], Ea-Wha Kang[3], Tae-Ik Chang[4], Yong-Kyu Lee[5], Kyung-Sook Park[6], Seok-Young So[7], Seung-Hyun Kim[8], Byung-Jun Bae[9], Jeong-Yeol Baek[10], Sug-Kyun Shin[11*], Miyeon Kim[12], Young-Ho Park[13*]

Abstract

This study seeks to evaluate the ability of machine learning methods to predict the dry weight of chronic hemodialysis athletes. The researcher has reached out to kidney patients who have had to give up sports and athletic careers due to chronic hemodialysis. This paper explores the development of medical prediction algorithms that combine image analysis with numerical data, which is widely used in the field of medicine. This deep learning method is widely employed to enhance the treatment of athletes who have kidney conditions. Regular hemodialysis is crucial for maintaining the health of athletes who have kidney disease. Accurately predicting dry weight is a crucial step in the process of performing hemodialysis. In this context, dry weight refers to the optimal moisture level at which excess water is effectively eliminated from the patient (athletes) through ultrafiltration during hemodialysis. In order to accurately determine the optimal amount of hemodialysis, predicting the correct dry weight is crucial. However, this task is quite challenging and often yields inaccurate results due to the extensive data analysis required by experienced nephrologists. This paper presents a deep learning methodology utilising the Artificial Neural Network (ANN) approach to efficiently address these issues. The proposed method aims to predict dry weight rapidly by analysing image values and clinical data from X-ray images obtained during routine check-ups. The current study has several theoretical and practical implications. This study contributes to the existing literature on chronic hemodialysis and the dry weight of athletes, offering valuable insights to sports health organisations. By doing so, these organisations can effectively prepare to proactively evaluate the atypical health conditions of athletes.

Keywords: Dry Weight, Chronic Hemodialysis Patients, Kidney Patients, Ultrafiltration, Artificial Neural Network Model.

1. Introduction

Engaging in sports activities necessitates that an athlete maintains a consistent level of physical activity and prioritise their overall health (Neslihan, 2017). It is rare for athletes to require long-term hemodialysis, but there are various factors that can contribute to the development of chronic diseases in this population. Most athletes maintain a strong state of health throughout their careers. Sports health organisations have also focused on regular medical

[1] Department of Internal Medicine, College of Medicine, Institute of Kidney Disease Research, Yonsei University, Seoul, Republic of Korea. E-mail: escapology@naver.com

[2] Department of Internal Medicine, College of Medicine, Institute of Kidney Disease Research, Yonsei University, Seoul, Republic of Korea. E-mail: kimjae90@yuhs.ac.kr

[3] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: eawha@medimail.com

[4] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: tichang@yuhs.ac.kr

[5] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: medicorpio@naver.com

[6] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: Pks114469@nhimc.or.kr

[7] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: syso72@nhimc.or.kr

[8] Division of Nephrology, Department of Internal Medicine, National Health Insurance Service Medical Canter, Ilsan Hospital, Goyang-Si, Gyeonggi-do, Republic of Korea. E-mail: sskyun10@nhimc.or.kr

[9] The Corporation for medical data science, Seoul, Republic of Korea. E-mail: manbi@kaist.ac.kr

[10] The Corporation for medical data science, Seoul, Republic of Korea. E-mail: baibj19@naver.com

[11] AI Research Team AIxX Corp, Seoul, Republic of Korea. E-mail: vabel100@chol.com

[12] Department of Airline Hospitality Services, Seoyeong University, Republic of Korea. E-mail: myk@seoyeong.ac.kr

[13] Divison of Artificial Intelligence Engineering, Sookmyung Women's University, Yong-San, Seoul, Republic of Korea. E-mail: yhpark@sm.ac.kr

*Co-correspondence: yhpark@sm.ac.kr (Y.-H.P.), sskyun10@nhimc.or.kr (S.-K.S.)

check-ups for athletes, proper hydration management, appropriate medication usage, and promoting a healthy lifestyle (AMSSM Collaborative Research Network Youth Early Sport Specialization Summit et al., 2022; Neslihan, 2017). These measures allow sports health organisations to monitor the overall health of athletes throughout their careers.

Therefore, the occurrence of kidney or other related diseases can be avoided. Athletes, like the general population, can also have pre-existing medical conditions that can lead to kidney diseases (Rojas-Valverde et al., 2019). Some examples of these conditions are autoimmune disorders, polycystic kidney disease, and congenital kidney abnormalities. In addition, rigorous physical training in hot and humid conditions can lead to heat stress and dehydration (Matias et al., 2023). Prolonged dehydration can strain the kidneys and potentially contribute to kidney damage. The accurate determination of dry weight in hemodialysis athletes is crucial for their prognosis (Liu et al., 2020). Efforts to enhance the accuracy of measuring dry body weight have been replicated, yet they continue to rely on clinical indicators and the expertise of experienced kidney physicians.

In addition, the studies have predominantly concentrated on patients with kidney conditions in general. Based on current research, there is a lack of studies specifically examining the effects of chronic hemodialysis on athlete (Brown et al., 2021; Mori, 2021; Pretto et al., 2020; Rahman & Pradido, 2020; Wilkinson et al., 2020). It is crucial for sports health organisations to diligently oversee the health and well-being of athletes. This study addresses the lack of research on professional athletes and chronic hemodialysis. It provides insights for sports health organisations on how to mitigate these issues among athletes. Relevant factors for predicting clinical dry body weight include pre-dialysis body weight, total body water, cardiac function, serum albumin concentration, systemic inflammatory status, inter-dialysis weight gain, degree of anaemia, chest X-ray photograph, findings of systematic or pulmonary edoema, and other related factors.

Numerous studies have been conducted to explore the potential of precise body water measurements in hemodialysis patients for predicting dry weight. A technique known as deuterium dilution can be used to measure the volume of water in the entire body. However, this method is not practical due to the need for radiation exposure, equipment preparation, and high costs. By contrast, multi-frequency bio-electrical impedance testing is becoming more prevalent for measuring additional body fluid compartments in a straightforward and secure manner (Di Iorio et al., 2004).

Certain drugs used by athletes to enhance performance, especially those used illicitly, can have negative effects on the kidneys over time (Piacentino et al., 2022). These drugs can cause kidney damage in athletes. In certain instances, it can also result in chronic kidney diseases among professional athletes. Excessive use of nonsteroidal anti-inflammatory drugs, like NSAIDs, can lead to kidney diseases in athletes (Brennan et al., 2021; Machado et al., 2021). Nevertheless, as a result of training or rigorous exercise, athletes frequently turn to NSAIDs to alleviate pain and reduce inflammation associated with sports injuries. Extended and excessive use of NSAIDs may lead to kidney damage, as stated by Drożdżal et al. (2021). Additional traumatic injuries, especially those that cause blood loss or muscle damage, can lead to complications that may also impact the kidneys. Certain athletes may have a genetic inclination towards kidney diseases, which can become apparent over time.

Within the context of MF-BIA, the flow of electrical current occurs within the cell. Measurement of intra-cellular resistance is used to estimate the water content within cells. The accuracy of these techniques in estimating total body water (TBW) has been demonstrated in various groups, such as healthy individuals, obese individuals, and patients with chronic kidney disorders (Cha et al., 1995; Martinoli et al., 2003).

Body composition is a crucial factor in the performance of professional athletes. It is valuable to consider the distribution of water in the body. To achieve optimal performance, athletes must ensure they maintain proper hydration levels. MF-BIA can offer valuable insights into the water content within cells. It can help athletes and sports professionals more effectively monitor hydration levels compared to traditional methods. Additionally, it has applications in evaluating muscle mass. Athletes, especially those involved in strength and power sports, may find it beneficial to track muscle mass fluctuations. MF-BIA can effectively estimate the intra-cellular water content and muscle mass of athletes in a non-invasive manner.

Extensive research has been conducted about hemodialysis patients and their dry body weight. However, it is worth noting that there is a lack of research specifically examining the impact of chronic hemodialysis on athletes, including its causes and implications for sports health organisations. The primary goal of these organisations is to guarantee the implementation of necessary preventive measures to safeguard the health and well-being of athletes (Johnson et al., 2020; Lin et al., 2023). In addition, the intense training in hot and humid weather conditions, as well as dehydration, can also impact the kidneys of athletes.

This study aims to assess the prediction of dry weight in chronic hemodialysis athletes to bridge the research gap and enhance the originality of the research. This study aims to improve the accuracy and customisation of fluid management protocols for athletes by using a machine learning approach to predict dry weight.

It is crucial to achieve an optimal dry weight to reduce the risks of complications related to hemodialysis. These factors include low blood pressure and stress on the heart. This study has significant implications for both professional athletes facing chronic kidney diseases and the sports health community. It contributes to their well-being and highlights broader health considerations. Accurate dry weight prediction using machine learning can enhance personalised interventions and optimise hydration strategies. In addition, it can improve the overall health and performance outcomes for athletes. By adopting this approach, one can effectively navigate the challenges posed by chronic hemodialysis and athletic pursuits.

2. Literature Review

Despite having knowledge about the water status of these patients, the clinical application to dry weight can be influenced by multiple factors. The cardiac function and the state of water in the blood vessel can vary depending on the nutritional state or presence of infections. To determine the dry weight, clinicians typically rely on measurements such as changes in blood pressure, chest X-ray images, pulmonary edoema or cardiovascular findings, and a process of trial and error. Objective methods, such as measuring the diameter of the inferior venacava or assessing the cardiac thoracic ratio (CTR) in chest photographs, have been utilised. However, these methods pose challenges in accurately determining dry weight with a single treatment in a clinical setting. Artificial intelligence is a complex system composed of interconnected computational elements, including machine learning and simulations of biological neural systems. It utilises associative functions and linear computations to model and mimic the behaviour of neurons (Chong et al., 2003; Guan, Huang, & Zhou, 2004). Neurons within a network can receive either inhibitory or excitatory signals from their neighbouring neurons. The Artificial Neural Network (ANN) model can identify and understand the connections between input signals and output, even when the data may not initially appear to be related. In addition, ANNs have been found to potentially outperform existing statistical methods (Forsström & Dalton, 1995) due to their learning algorithms. This can be utilised to assess the effectiveness of dialysis (Gabutti et al., 2004; Guh et al., 1998), as well as for diagnosing and predicting the progression of nephropathy (Geddes et al., 1998; Rajimehr et al., 2002), issues and challenges related to kidney transplantation (Abdolmaleki et al., 1997; Brier, Ray, & Klein, 2003).

In a recent study, Guo et al. (2021) investigated the impact of ageing on mastication and its effect on the dry weight composition. The model utilised in this study is the MKSVRMAS model. It served as a predictive model for estimating the dry weight of dialysis patients at that location. The study utilised three distinct forms of data. In the study, data from structural statistics, anthropometric measurements, and resurrected spectroscopy were collected and utilised. This paper utilises different data than the ones mentioned. Additionally, it possesses an efficient method for inputting data. The provided data served as input for the calibration process. Documents and grades that do not utilise object big data have been discovered. Ultimately, our study focuses on machine learning techniques, specifically in predicting dry weight. It is important to note that our research does not rely on data used for dialysis.

This paper presents a unique approach as it utilises real data collected from dialysis patients at Ilsan Hospital during the dialysis process. In a study conducted by Hae et. al., they examined the issue of BIS being inaccurately portrayed as within the range of clinically normal weight (Guo et al., 2021). Thus, in order to address this issue, a machine learning approach is employed utilising the patient's clinical data and BIS as a key indicator. In this study, our objective was to predict an optimal dry weight for clinical purposes. The machine learning method employed in the paper exhibits similarities, albeit with variations in the nature of the data being processed. When comparing the thesis to a study on general dry weight, there are notable differences. Our research focuses on analysing the impact of dry weight using data collected during the dialysis procedure. Our paper presents a range of findings related to hay weight changes during dialysis.

This method differs from the proposed approach. We examined dialysis dry weight using machine learning and deep learning techniques, highlighting the distinctions between the two approaches. In this section, we have examined the contributions and distinctions of the proposed thesis based on the studies. The thesis concludes with a section dedicated to the discussion of related works. Before delving into this study, it is important to examine relevant studies (necessity, purpose, method). A comprehensive analysis of the technical components will be conducted in the Related Works and Discussion section towards the end of the thesis.

This study utilises artificial intelligence to establish the correlation between each indicator and the predicted body weight. It aims to assess the accuracy of dry body weight prediction using the selected model based on post-learning.

2.1. Terminologies and Implementation for Measuring Dry Weight

In this section, we will present the implementation details pertaining to the measurement of dry weight using actual patient datasets.

2.1.1. Input Parameters and Terminologies

In general, the clinical parameters used to determine the appropriate dry weight for hemodialysis athletes are as follows:

• Chest X-ray

The health of a person's cardiovascular system can have an impact on their weight. The ratio of the thoracic and cardiac sizes is converted to the Cardiac thoracic ratio (CTR) and used as a metric. A higher click-through rate could indicate potential issues with cardiac function or excessive water retention.

• Blood albumin concentration

In normal subjects, the effectiveness of blood albumin concentration on dry body weight is reduced. When the blood albumin concentration is below normal, it can lead to a decrease in blood osmolality, which in turn may make it challenging to effectively remove excess water and lower blood pressure. Thus, hypo-albuminemia should not be disregarded as it plays a significant role in hindering precise weight measurements.

• Degree of anemia

Anemia can be evaluated by measuring hemoglobin or hematocrit levels. Anemia is a common occurrence among patients undergoing dialysis. It is possible that the necessary hematopoietic agent is not given or that the agent is resistant. If blood is depleted too quickly due to water removal from blood vessels, it can result in hypotension. Thus, anemia could potentially hinder the maintenance of a healthy weight.

• Dry weight of previous hemodialysis

It is crucial to consider the process of the previous dialysis. If blood pressure continues to rise during dialysis, it indicates an excessive amount of body water. When dialysis begins, it is possible for the body weight prior to the procedure to be lower than the dry body weight if the blood pressure is reduced. In such a scenario, the dry weight is adjusted slightly. Hence, the measurement of the dry weight following the previous dialysis session will play a crucial role in determining the appropriate dry weight for the subsequent dialysis treatment.

• Changing pattern of blood pressure on hemodialysis

Understanding fluctuations in blood pressure is crucial for determining the appropriate dry weight. If blood pressure decreases upon initiation of dialysis, it indicates that the pre-dialysis body weight is already below the dry body weight. In this situation, dialysis is necessary to promote weight gain in the body. When the blood pressure decreases during dialysis, it is important to reassess and potentially readjust the dry weight. When the blood pressure decreases after dialysis, it is important to consider adjusting the dry weight. It is important to also consider if the amount of water removed during dialysis is excessive, as well as other potential factors such as infectious diseases or cardiac function weakening.

• BUN levels

Excessive uremia can arise from insufficient dialysis or an exaggerated physiological reaction to urea synthesis. For instance, it can increase in dry conditions or because of an exothermic reaction caused by gastrointestinal bleeding or infectious diseases. Furthermore, it can be stated that the decrease is in a state of either nutritional deficiency or excess water.

• Creatinine levels

As creatinine levels rise, renal function declines, leading to reduced or absent urine output. This factor is of significance as it hampers the regulation of water conditions (Cooper et al., 2000).

• Pre-dialysis weight

Prior to dialysis, weight is a crucial factor in determining the amount of water that needs to be removed from the dry weight. Weight gain during the period between dialysis sessions can contribute to an increase in dry weight. On the other hand, the measurement of dry body weight is crucial as it can be influenced by various factors that may lead to a reduction in its value.

3. Research Methodology

3.1. Collection of datasets

Given the focus on professional athletes, the researcher examined individuals who had to retire from their careers due to the prevalence of hemodialysis. The researcher chose individuals who had been athletes for a decade. Data was collected from January 1, 2011, to December 31, 2018, for athletes who received hemodialysis as outpatient treatment at Ilsan Hospital. The data set was collected in a systematic manner, encompassing various measurements such as chest X-ray, pre-dialysis weight, dry weight determined after dialysis, post dialysis weight, mean arterial pressures between dialysis, BUN, Cr, Hb, HCT, and albumin.

3.2. Calculation of CTR from chest X-ray

The calculation of CTR involves dividing the sum of MRD and MLD by ID. The MRD and MLD represent the maximum transverse diameters of the right and left sides of the heart. These measurements are obtained by drawing lines from the midline of the spine to the furthest points of the right and left cardiac margins. The ID represents the largest internal diameter of the thorax. The initial step involved performing lung segmentation on the chest X-ray to enable the automatic estimation of MRD, MLD, and ID. The segmentation model was created using a convolutional neural network and trained on a dataset of 7,470 chest X-ray images from the National Library of Medicine.

After segmenting the lung areas, a noise detection process was applied to eliminate small portions that are far away from the main segmented area. A midline of the spine (ML) was positioned between the right and left sides of the lungs. At each vertical point, the horizontal distances from ML to the nearest border of each right and left segmented area were calculated. Horizontal distances were compared to detect sudden changes in distance, allowing for the prediction of the vertical boundaries of the heart area. Finding the greatest distances within the heart region allowed for the estimation of the MRD and MLD. The methods outlined in this paper require an average of 40 seconds to segment and calculate the CTR for a single chest X-ray image. In contrast, manual measurement and calculation take over a minute, as depicted in Figure 1.

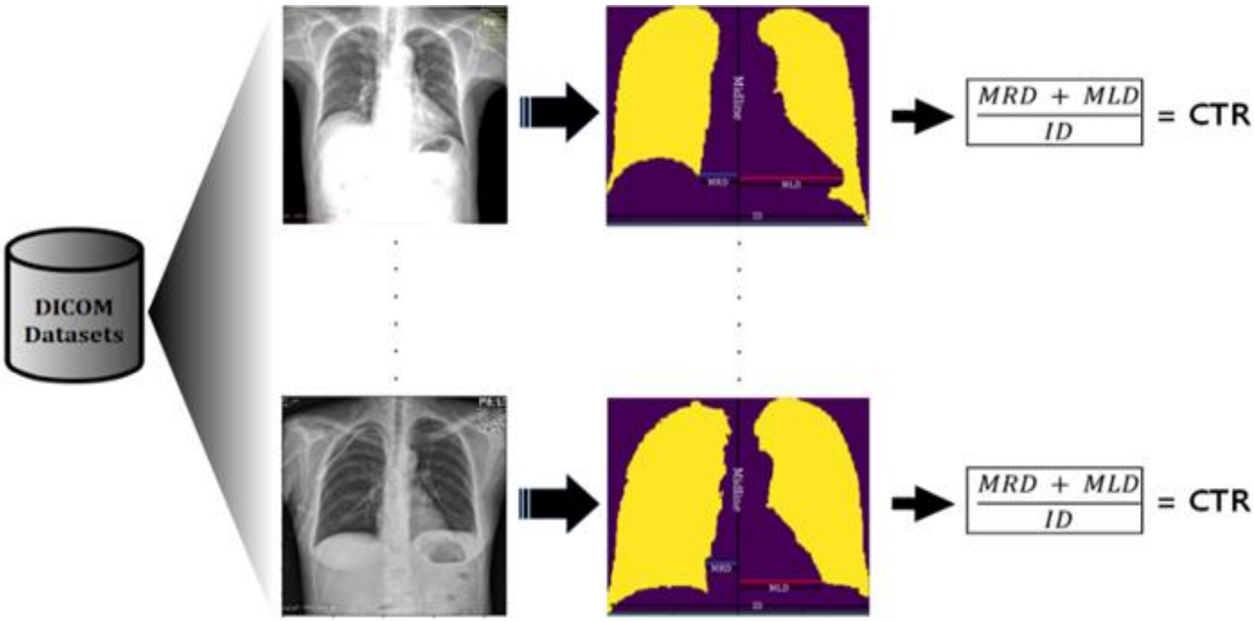


Figure 1. Process of Lung Segmentation and CTR Calculation.

4. Results

4.1. Pre-Processing Datasets

53,925 hemodialysis cases made up the raw EMR data from Ilsan Hospital in the Republic of Korea, South. Dialysis patients with hemoglobin (Hb) levels below 7.5 were not accepted. Hb was expressed in g/dL. The unit of measurement for blood urea nitrogen (BUN) was mg/dL; BUN values of 30 or less and 100 or more were not included. Blood pressure (BP) was measured in mmHg using the mean arterial pressure as a reference. Dialysis cases with a systolic blood pressure of more than 200 or less than 70 were not included. Following this laboratory data cleansing, 46,937 instances were still present (Krouwer & Monti, 1995).

Next, the remaining dialysis cases were filtered once more, this time only including cases where: i) the weight after dialysis is equal to or less than the weight before dialysis; ii) the weight difference between the pre- and post-dialysis weight is equal to or less than 4 kg; iii) the CTR is less than 0.625; and iv) the weight difference between the dry weight and the dry weight from the previous dialysis is equal to or less than 500g. In Table 1, the final dataset for regression analysis included a total of 39,449 dialysis cases from 317 patients. On average, each patient underwent dialysis 124 times.

A random sampling technique was employed to divide the data set into approximately 80% for training purposes and 20% for testing purposes. The training data included a total of 31,893 samples and was fed into different machine learning algorithms to acquire knowledge and make predictions regarding the dry weights. The test data set comprised 7,556 samples and was utilised to assess the performance of the trained regression models.

Table 1

Distribution of Input Variables.

Features	Units	Mean	Standard Deviation	Range
Age	years	59.6 (95% CI 59.5 to 59.8)	12.49	15 ~ 91
Pre-dialysis weight	kg	61.2 (95% CI 61.1 to 61.3)	10.59	33.3 ~ 99.7
dry weight (prev.)	kg	59.1 (95% CI 59.0 to 59.2)	10.39	32 ~ 96.5
BP (beginning)	mmHg	144.4 (95% CI 144.2 to 144.6)	19.93	70 ~ 200
BP (Middle)	mmHg	142.6 (95% CI 142.4 to 142.8)	19.87	70 ~ 200
BP (last)	mmHg	137.9 (95% CI 137.7 to 138.1)	20.84	70 ~ 200
Albumin	g/dL	3.388 (95% CI 3.384 to 3.392)	0.39	1.4 ~ 4.9
Hb	g/dL	10.659 (95% CI 10.655 to 10.663)	1.21	7.5 ~ 16.3
NA	mEg/L	137.12 (95% CI 137.09 to 137.15)	2.98	120 ~ 147
BUN	mg/dL	56.16 (95% CI 56.01 to 56.30)	14.67	30 ~ 100
ctr	-	0.4018 (95% CI 0.4016 to 0.4019)	0.02	0.265 ~ 0.624

4.2. Dataset and Pre-Experiments

Another set of data we utilised includes the requirement for South Korean athletes to subscribe to health insurance. The data utilised was obtained from Ilsan Hospital, which is operated by the National Health Insurance Corporation. The data provided by Ilsan Hospital consists of dialysis data for patients with kidney disease. Personal information was redacted from the data to ensure the protection of sensitive data. Furthermore, the data utilised was transformed in a manner that prevents the identification of any individual through the combination of data. All athlete and patient data are consolidated into a comprehensive dialysis patient information database, which is then utilised for analysis purposes.

The data generated during the dialysis process by patients was stored in the database. The stored data is approximately 17.5 GB in size, and it contains the results of dialysis for 500 athletes. The database that stores information about the dialysis process varies in terms of the frequency and details of dialysis, depending on the individual patients who underwent the procedure. Here is the following information: Figure 2 displays the databases. The image in the top left corner of the figure displays the database tables utilised in the dialysis data of patients. The image in the upper right corner of the figure illustrates the sequence of steps: 1. Retrieve the identification numbers of athlete patients. 2. Retrieve the session identification numbers for all athlete patients. During the session, treatment data should be extracted. The image at the bottom of the figure displays the concatenation of all treatment data for the athlete patient. In this experiment, we only combined the data of 500 athlete patients.

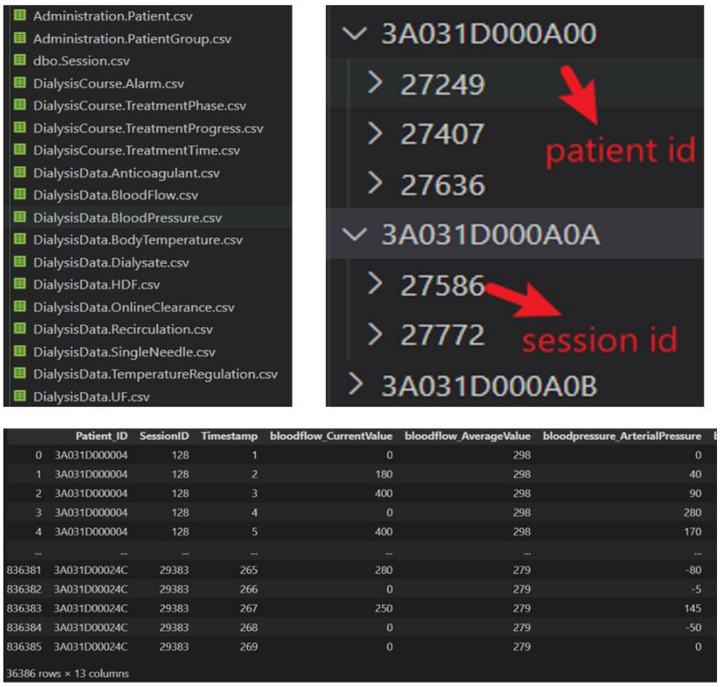
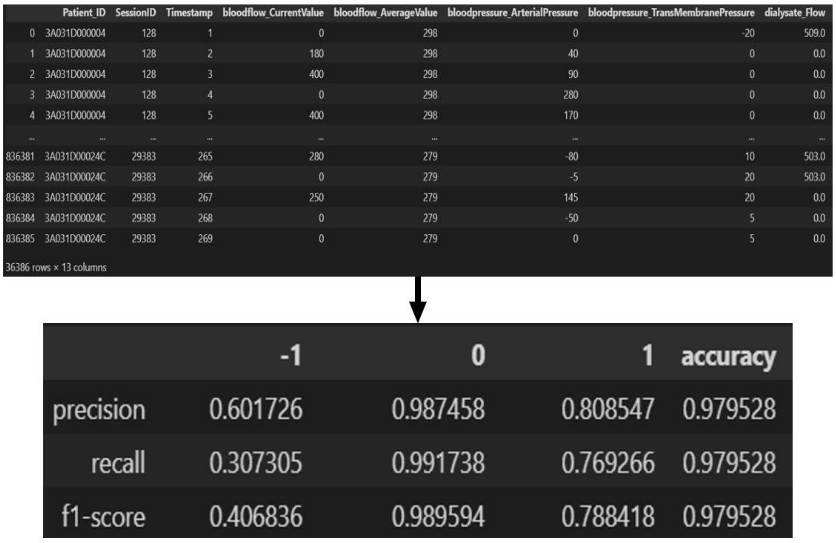


Figure 2. Original Databases: Schemas and Instances.

The data stored in the database includes the patient's blood pressure predictions and dry weight measurements over time. In this paper, the data was analysed using different methods prior to conducting the dry weight analysis. Initially, the number of athlete patients was determined based on data collected during their dialysis procedure. Figure 3 displays the classification of blood pressure into three categories: (1) high, (2) low, and (3) normal. This classification was achieved through the automatic classification of the information stored in the database. It was assumed that the distribution of blood pressure followed a normal distribution. As per the data analysis, approximately 95% of the measured values fall within the normal range. The portion on the left, specifically the left 2.5% of the normal distribution, was categorised as having low blood pressure. According to the data, the right side of the normal distribution, specifically the left 2.5%, was identified as having high blood pressure.



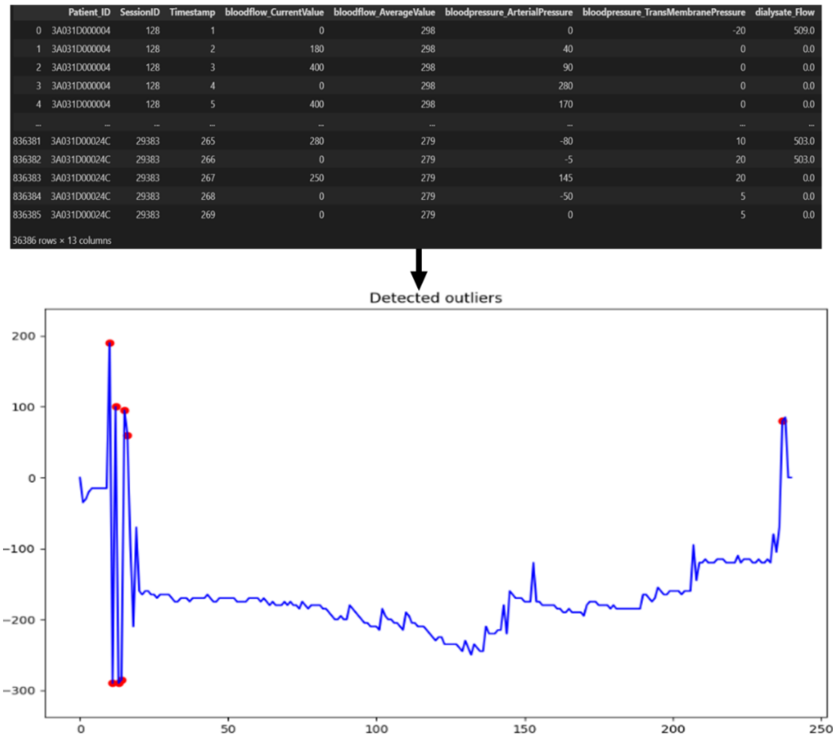
	Patient_ID	SessionID	Timestamp	bloodflow_CurrentValue	bloodflow_AverageValue	bloodpressure_ArterialPressure	bloodpressure_TransMembranePressure	dialysate_Flow
0	3A031D000004	128	1	0	298	0	-20	509.0
1	3A031D000004	128	2	180	298	40	0	0.0
2	3A031D000004	128	3	400	298	90	0	0.0
3	3A031D000004	128	4	0	298	280	0	0.0
4	3A031D000004	128	5	400	298	170	0	0.0
...	...	...	...	...	...	...	...	...
836381	3A031D00024C	29383	265	280	279	-80	10	503.0
836382	3A031D00024C	29383	266	0	279	-5	20	503.0
836383	3A031D00024C	29383	267	250	279	145	20	0.0
836384	3A031D00024C	29383	268	0	279	-50	5	0.0
836385	3A031D00024C	29383	269	0	279	0	5	0.0

36386 rows × 13 columns

	-1	0	1	accuracy
precision	0.601726	0.987458	0.808547	0.979528
recall	0.307305	0.991738	0.769266	0.979528
f1-score	0.406836	0.989594	0.788418	0.979528

Figure 3. Classification According to Blood Pressure.

Furthermore, this paper presents the derived ideal measurement value of the data. By analysing the provided data, we were able to identify fluctuations in blood pressure that occur during the dialysis procedure. This allows us to proactively detect potentially hazardous situations that patients may face. The process is illustrated in Figure 4 below.



	Patient_ID	SessionID	Timestamp	bloodflow_CurrentValue	bloodflow_AverageValue	bloodpressure_ArterialPressure	bloodpressure_TransMembranePressure	dialysate_Flow
0	3A031D000004	128	1	0	298	0	-20	509.0
1	3A031D000004	128	2	180	298	40	0	0.0
2	3A031D000004	128	3	400	298	90	0	0.0
3	3A031D000004	128	4	0	298	280	0	0.0
4	3A031D000004	128	5	400	298	170	0	0.0
...	...	...	...	...	...	...	...	...
836381	3A031D00024C	29383	265	280	279	-80	10	503.0
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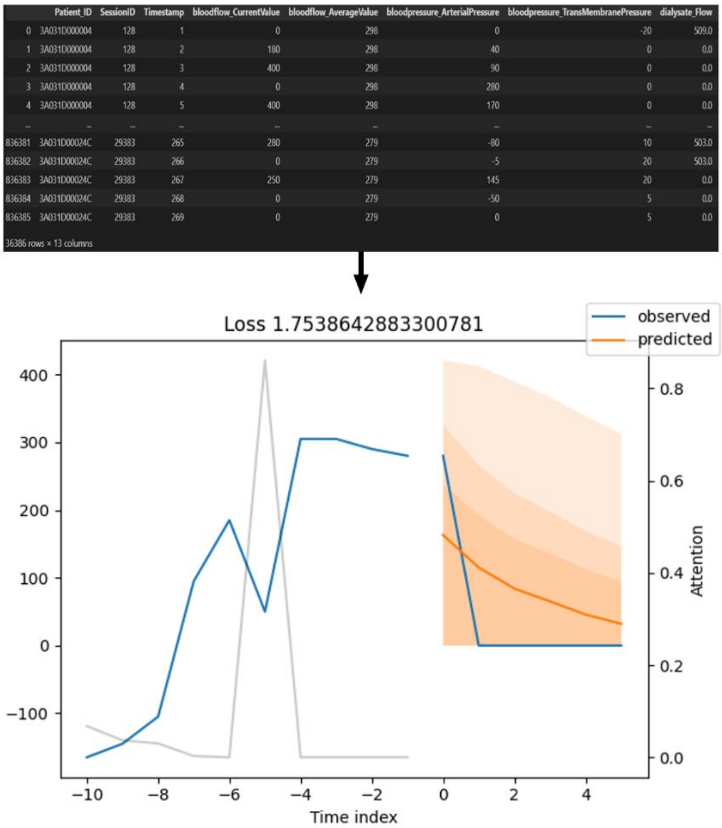
836383	3A031D00024C	29383	267	250	279	145	20	0.0
836384	3A031D00024C	29383	268	0	279	-50	5	0.0
836385	3A031D00024C	29383	269	0	279	0	5	0.0

36386 rows × 13 columns

Figure 4. Abnormalities in Blood Pressure That Occur During the Dialysis Process.

In this paper, we present the prediction of blood pressure in athlete patients during dialysis and after 6 minutes using the deep learning TFT (Temporal Fusion Transformer) method, specifically the transformer method. The calculation of the patient's blood pressure range was completed after a duration of 6 minutes. By conducting this analysis, it became feasible to identify any atypical indications of the patient's blood pressure that could manifest over time. The prediction of blood pressure holds immense importance in the context of dialysis, as it is widely regarded as a critical factor. When predicting the blood pressure of a patient during dialysis, there is a significant advantage in being able to identify and handle potentially hazardous situations that may arise in the near future. Figure 5 displays the experimental results obtained from our conducted experiments. The lower figure in Figure 5 displays the projected outcomes.

The deep learning model, TFT, presents the prediction result as a range. By utilising this feature, users can determine the expected range of the prediction outcome. The solid line shown in orange represents the predicted value, while the shaded area in orange indicates the range of predictability. Within the spectrum of orange range expressions, it is evident that the intensity of the colour corresponds to the number of results encompassed. However, the information highlighted in blue represents the precise measured value. The blue solid line does not precisely align with our predicted value, but it is evident that the result falls within the predicted range. It was demonstrated that the fluctuation in blood pressure following a six-minute period can be somewhat anticipated using TFT, a Deep Learning Transformer model.



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3	3A031D000004	128	4	0	298	280	0	0.0
4	3A031D000004	128	5	400	298	170	0	0.0
...	...	...	...	...	...	...	...	...
836381	3A031D00024C	29383	265	280	279	-80	10	503.0
836382	3A031D00024C	29383	266	0	279	-5	20	503.0
836383	3A031D00024C	29383	267	250	279	145	20	0.0
836384	3A031D00024C	29383	268	0	279	-50	5	0.0
836385	3A031D00024C	29383	269	0	279	0	5	0.0

36386 rows × 13 columns

Figure 5. Patient's Blood Pressure Was Predicted During Dialysis and After 6 Minutes Using the Deep Learning TFT**.**

4.3. Model and Experimental Results

In this section, we will discuss the models of learning algorithms that were used and how the results of the algorithms were validated.

4.3.1. The result of pre-processing

The typical range for blood sodium (Na) levels is 135 to 145 mEq/L, according to Chernecky and Berger (2012). Approximately 17% of the samples in the train and test data exhibited blood sodium levels that deviated from the normal range. The BUN level and albumin have a reference range of 3–20 mg/dL and 3.5–5.5 g/dL, respectively (Dossetor, 1966). It is worth noting that 99% to 100% of the sampled data fell within this range. In adults, the hemoglobin concentration reference range is 12.3–17.5 g/dL, as reported by Henry (1996). Interestingly, a significant 91% of the cases fell outside this established range. A CTR greater than or equal to 0.5 is considered abnormal, indicating that values lower than this are considered normal (Panju et al., 2002; Rubens, 1996), and only about 1% of the total samples were estimated to be abnormal. Approximately 18% of the total data consisted of dialysis cases where the difference between the dry weight and the dry weight of the previous dialysis exceeded 150g.

4.3.2. Models of learning algorithms

The following factors were considered: patients' age, gender, pre-dialysis weight, dry weight of the past dialysis, BP measurements during the first, middle, and last periods of the previous dialysis, the dialysis patients' albumin, Hb, Na, and BUN levels, and finally, CTR. We studied and evaluated various machine learning regression algorithms, such as multi-layer linear regression, ridge regression, lasso regression, and ANN, on the given dataset. To achieve optimal performance on our data, a neural network architecture with three layers was employed. This architecture is comprised of two hidden layers and one output layer. The network was designed with 12 inputs and 7 neurons in each hidden layer. The output indicates the optimal dry weight for the dialysis procedure. The rectified linear unit function was employed to activate the hidden layers. The back-propagation algorithm utilised for training the network was the Limited Broyden-Fletcher-Goldfarb-Shanno algorithm. Figure 6 illustrates the learning process of this ANN model.

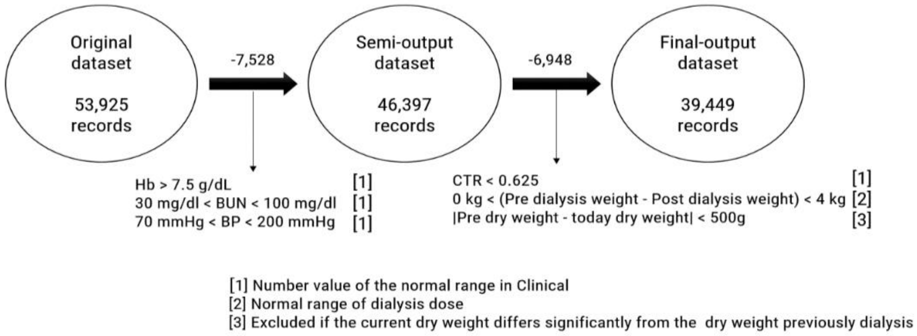

Figure 6. Pre-Processing Dataset.

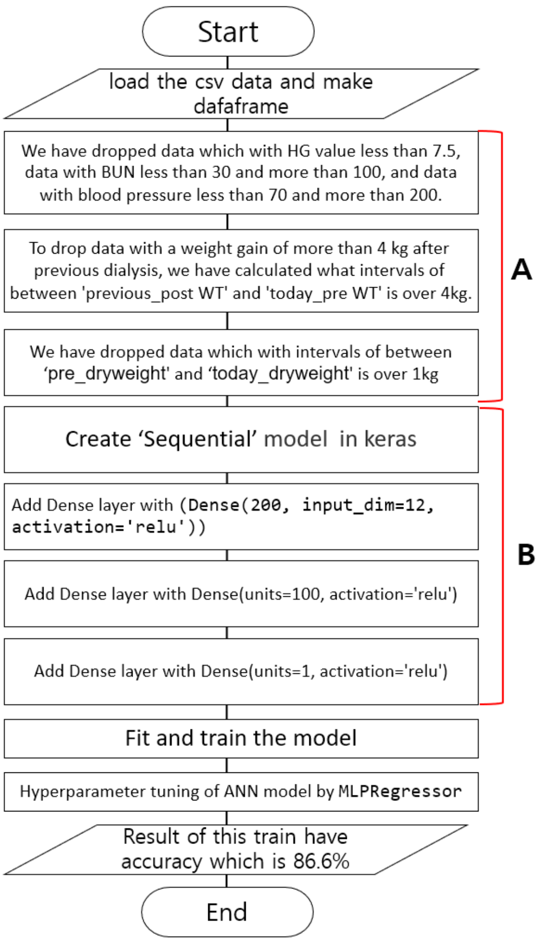

Figure 7. Pre-Processing Dataset.

4.4. An algorithm for Constructing the Model

Figure 7 illustrates the process of constructing a model that implements the method described in this paper and obtaining the corresponding outcomes. This is a visual depiction of an algorithm. To begin, data is loaded to create a data frame. Finally, after progressing through multiple stages, the desired outcome is achieved. The label on the right side of Figure 7 indicates "Data Pre-processing". Additionally, label B below outlines the process of creating an ANN model, known as the "Create ANN Model" process. By following the recommended steps, A and B sequentially, you can fine-tune the hyperparameters of the ANN model using the MLPRegressor. During the learning process, the train's result achieves an accuracy of 86.6%.

4.5. Result Validation of Learned Algorithms

The performance of the regression model was assessed by comparing the predicted dry weights of the dialysis cases with the actual dry weights from the test set. For a given dialysis case, the dry weight prediction was deemed accurate if the discrepancy between the predicted dry weight and the actual dry weight was below 150g. Furthermore, those predictions were deemed inaccurate. The three-layer ANN regression model achieved the highest accuracy of 86.6%, as depicted in Figure 8. It outperformed the linear regression, ridge regression, and lasso regression models, which achieved accuracies of 86.4%, 86.3%, and 72%, respectively.

The Results

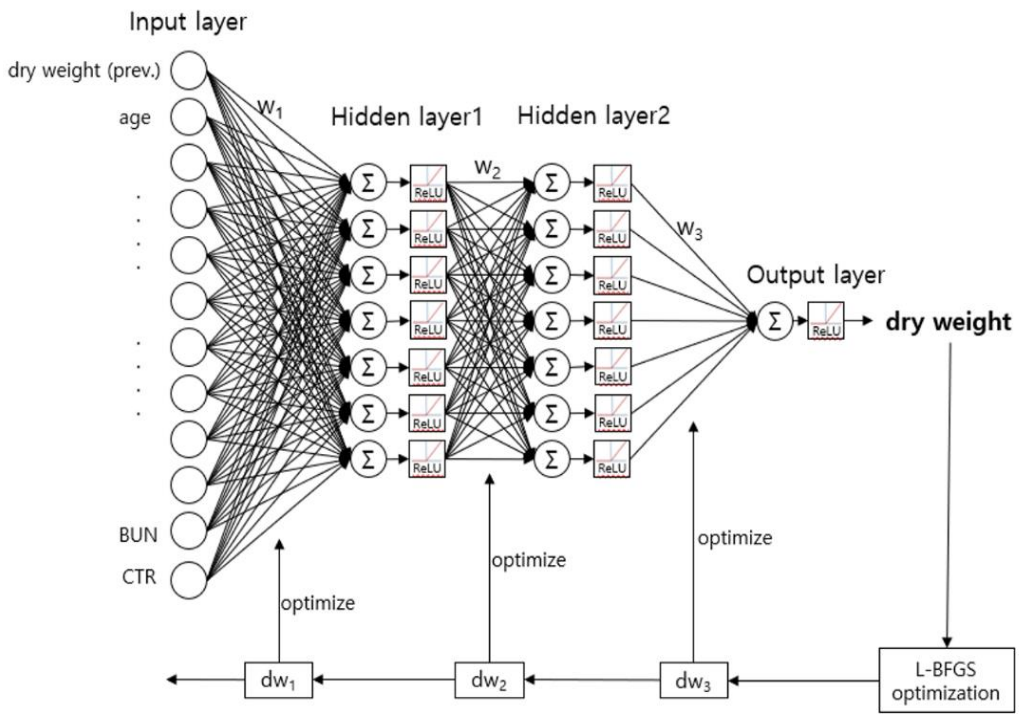

Figure 8. Workflow of Three-Layer Neural Network Regression Model.

5. Discussion

The objective of this study was to evaluate the dry weight of professional athletes undergoing chronic hemodialysis. To achieve this objective, the implementation of a machine learning approach was carried out. The researcher conducted a study involving individuals who had been diagnosed with chronic kidney disease, specifically those who were athletes and undergoing hemodialysis treatment. Following the implementation of various methodologies, the findings were derived. The CTR was determined by analysing the chest X-ray. In addition, conclusions were derived from the model and experimental data. The researcher also utilised models of learning algorithms. Currently, in the clinical setting, there is a practical approach to determining the dry weight of hemodialysis patients who have a background in athletics. This involves a systematic process of trial and error. Due to the significance of dry weight, numerous nephrologists have conducted research on more precise measurement techniques. While there are ways to objectively measure dry weight, there are certain limitations to their direct application in clinical settings.

One significant advancement is the bio-impedance measurement technique, which accurately quantifies the water content within patients' bodies. In a study conducted by Chamney et al. (2002), a technique for measuring dry weight using whole body bio-impedance was introduced. It was proposed that by intersecting slopes (SHV with SNV) through BIS, a potential new method for predicting Dry Weight could be identified. However, measuring bio-impedance in clinical situations proved to be challenging, which limited its widespread use. Subsequently, numerous scholarly articles have been published regarding the utilisation of machine learning algorithms for the regulation of dry weight. In a recent study by Kim et al. (2021), the researchers aimed to predict dry weight by analysing BIS data alongside different clinical indicators. In this study, the data required to measure BIS was also collected. To analyse this data, a decision tree-based methodology called LightGBM, which is suitable for table-type medical data, was used. Additionally, the XGBoost and random forest methods were also employed.

Ultimately, it is widely acknowledged that machine learning is a more practical approach for predicting DWCP compared to DWBIS, except for certain specific circumstances. However, there were limitations observed in terms of significant differences in cardiac function or malnutrition status. Conversely, research has been conducted to quantify the dry weight of paediatric patients. Unlike adults, paediatric patients present unique challenges when it comes to predicting their dry weight. This is due to the complexities of their condition. In a study conducted by Niel et al. (2018), the authors examined the effectiveness of two different methods for predicting dry weight in paediatric patients undergoing hemodialysis.

One method involved the use of artificial intelligence, while the other relied on the measurements taken by an experienced nephrologist. The study involved the design of a neural network that considers bio-impedance, blood volume monitoring, and blood pressure values as input. Based on the study findings, the Neural Network concluded that its predictions outperformed those of experienced nephrologists in most patients. It suggests that this could be a promising new approach for predicting dry weight.

We require an artificial intelligence algorithm capable of accurately predicting dry weight for clinical use within a hemodialysis room. Thus, the researchers attempted to forecast the dry weight by utilising a data-driven approach along the same path that an experienced nephrologist uses to predict the dry weight. For Artificial Intelligence to understand human intelligence, it was necessary to analyse the actions and methods employed by skilled nephrologists in determining and quantifying dry weight. Medical professionals typically begin by reviewing the patient's most recent dialysis records. Simply stated, if there was no change in blood pressure at the last measurement or if there was not a significant increase in body weight between dialysis sessions, the general trend was to maintain the same weight. If cardiomegaly is observed in the chest x-ray, physicians may recommend reducing the dry weight. When blood pressure decreases during dialysis, it is necessary to raise the dry weight. When blood pressure is elevated, it results in a reduction in dry weight. Controlling the dry weight involves considering various parameters, including the severity of anaemia, the concentration of serum albumin, and the fluctuations in inter-dialysis weight gains, among others.

Table 2

Average Checkup Data by Age of Patients.

NO	age	today_pre WT	previous_post WT	pre_dry_weight	first	middle	last	Albumin	HG	NA	CR	ctr	today_dryweight
1	10's	70.88	69.76	69.82	151.83	151.51	146.67	3.84	10.22	136.33	11.82	0.40	69.80
2	20's	61.40	59.26	59.14	145.65	143.94	139.08	3.38	10.58	136.89	9.23	0.40	59.12
3	30's	61.40	59.25	59.13	145.64	143.92	139.07	3.38	10.59	136.91	9.27	0.40	59.12
4	40's	61.31	59.17	59.06	145.25	143.58	138.81	3.36	10.59	136.88	9.22	0.40	59.04
5	50's	61.43	59.30	59.18	145.21	143.52	138.76	3.36	10.60	136.90	9.20	0.40	59.17
6	60's	61.43	59.30	59.19	145.20	143.50	138.76	3.36	10.60	136.90	9.20	0.40	59.18
7	70's	61.45	59.31	59.19	145.23	143.53	138.75	3.36	10.60	136.90	9.21	0.40	59.18
8	80's	61.42	59.29	59.18	145.21	143.51	138.77	3.36	10.60	136.90	9.20	0.40	59.17
9	90's	61.36	59.21	59.15	145.27	143.49	138.35	3.38	10.63	137.10	9.43	0.40	59.14

The objective of this study was to utilise artificial intelligence to forecast dry body weight based on the clinical indicators mentioned earlier, as proposed by experts in the field of nephrology. In order to observe the change in the patient's weight and dry weight, Figure 9 displays the results of our model training using the patient's actual checkup data. Table 2 displays the average checkup data for each age group.

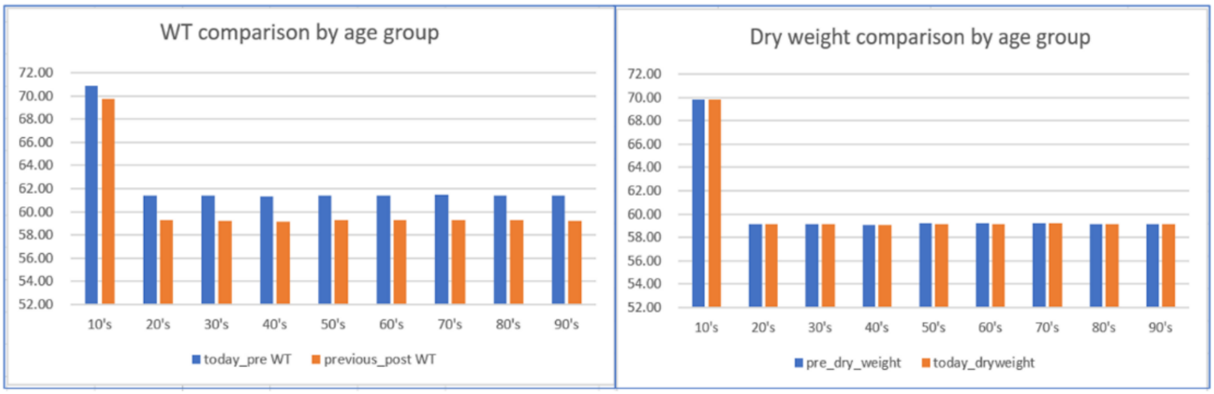

Figure 9. Dry Weight / WT Comparison by Age Group.

6. Conclusion

As a result of intense training in hot and humid weather conditions, among other significant factors, kidney diseases have become more prevalent among athletes. Nevertheless, following the diagnosis of these conditions, it is common for athletes to retire from their athletic pursuits. This study contributes to the existing body of literature by examining the incorporation of chronic hemodialysis in athletes, bringing a fresh perspective to the field. Researchers have specifically studied kidney patients who were former athletes and had to end their careers due to chronic hemodialysis. Several sports health organisations have been established to monitor the health and well-being of athletes. This study has significant implications for sports health organisations.

A recent report highlights the potential of artificial intelligence in accurately measuring dry weight through conducting similar studies in paediatric dialysis patients. Predictions can offer valuable reference points instead of solely focusing on determining dry weight. This could help streamline the process of starting treatment by calculating the dry weight of athletes in clinical settings or for dialysis nurses. Within a clinical setting, certain clinical data may prove to be extremely valuable in determining the appropriate dry weight for hemodialysis patients. This data often consists of numerical values that may fall outside of the normal range, either being too high or too low. High CTR values may suggest that patients have undergone pneumonectomy, experienced lung injuries, or have severe lung effusion in both lungs.

We have chosen to exclude these cases from our data evaluation process due to the inherent challenges in distinguishing them using chest X-ray and Artificial intelligence methods. In addition, haemoglobin, BUN, and serum albumin levels that were either too high or too low were not included in the evaluation data for similar reasons. We utilised a set of 12 features, encompassing weight attributes from previous dialysis sessions, blood pressure data, laboratory data, and CTR, to accurately forecast the optimal dry weight for dialysis treatment. This was achieved through the application of diverse regression algorithms within the realm of machine learning. The regression model with a layer size of 7 neurons achieved the highest dry weight prediction accuracy of 86.6%.

7. Research Implications

This study has both theoretical and practical implications. Below, you will find explanations for these:

7.1. Theoretical Implications

This study contributes to the theoretical basis of sports medicine by incorporating machine learning techniques in the management of athletes undergoing chronic hemodialysis. It provides opportunities to explore new technologies and models to tackle the intricate medical issues in the field of sports health. This study further enhances the theoretical comprehension of personalised treatment methods. This study emphasises the significance of customising medical interventions to meet the unique needs and physiological responses of athletes undergoing chronic hemodialysis. It achieves this by utilising machine learning to predict dry weight. In addition, the incorporation of machine learning to forecast dry weight also brings attention to other theoretical implications in the realm of biomedical informatics. This study promotes further investigation into data-driven approaches to enhance decision-making procedures in sports health and medical care.

7.2. Practical Implications

This research has significant practical implications as it has the potential to revolutionise the management strategies for athletes undergoing chronic hemodialysis. Machine learning predictions of dry weight can aid in personalised and precise adjustments for fluid removal during hemodialysis sessions. Additionally, it can help reduce the likelihood of complications. This study's findings can be applied to help reduce the risks associated with fluid imbalance in athletes undergoing chronic hemodialysis. An improved prediction model can also aid in the prevention of adverse events. These symptoms may include cramping, cardiovascular strain, and hypotension, which can enhance the safety of athletic participation.

This study offers valuable insights to the sports health organisation. Implementing machine learning can facilitate personalised fluid management and reduce the risks of complications during hemodialysis. This development is in line with the organization's objectives of enhancing the health and performance of athletes. Furthermore, it encourages personalised care and actively contributes to the wider realm of sports medicine. This can be accomplished using data-driven methods and innovative techniques. In addition, this study highlights the significance of regularly evaluating the health and well-being of athletes to ensure their overall welfare. Proactive prediction of dehydration enables the timely administration of necessary medications to athletes.

8. Research Limitations and Future Research Implications

This study has primarily examined professional athletes, which has restricted the researcher's focus to specific sports such as football, hockey, or cricket. Future researchers may choose to examine specific athletes to gain valuable insights into the underlying causes of chronic hemodialysis. A significant limitation of this study is that the determination of the true label of the dry weight relies entirely on the diagnostic methods employed by clinical physicians. The cases involving irregular blood pressure during dialysis were excluded in order to ensure that cases where physicians may have made a misdiagnosis of patients' dry weights were not included in the analysis. Nevertheless, there is no assurance that physicians' assessment of patients' dry weights was precisely optimal.

To enhance future work, it may be beneficial to utilise a feature selection technique. This technique would allow for the use of a reduced number of features as model input, while still achieving improved performance. In addition, more advanced machine learning algorithms or intricate models like deep learning can be utilised to enhance the performance of the model. Future directions for this study may involve the creation of real-time monitoring systems that incorporate machine learning. The fluid removal during hemodialysis can be adjusted dynamically for athletes, leading to improved precision in treatment. Furthermore, these findings may have implications for the incorporation of personalised healthcare technologies within sports health organisations. By adopting this approach, the overall well-being and performance of athletes undergoing chronic hemodialysis can be improved.

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