Engineering Solid Mechanics 13 (2025) 217-228

Contents lists available at GrowingScience

Engineering Solid Mechanics

homepage: www.GrowingScience.com/esm

Developing an artificial neural network-based tool to predict roughness parameters and cellular viability on surfaces of dental implant fixtures treated with the SLA+Anodizing method

Ehsan Anbarzadeh[a] and Bijan Mohammadi[a,b*]

[a]*School of Mechanical Engineering, Iran University of Science and Technology, Tehran, Iran*
[b]*Guest Researcher, Centre for Industrial Mechanics, Department of Mechanical and Electrical Engineering, Faculty of Engineering, University of Southern Denmark, Denmark*

A R T I C L E I N F O

Article history:
Received 8 June 2024
Accepted 18 December 2024
Available online
18 December 2024

Keywords:
Implant
Surface characterization
Artificial neural network
SLA+Anodizin

A B S T R A C T

This research pioneers the development of an innovative approach for refining dental implant fixture surfaces using the SLA+Anodizing method. Leveraging a rich dataset encompassing 68 distinct implant surface treatment states, the study employs an Artificial Neural Network (ANN) to predict crucial parameters such as surface roughness and cellular viability. Through meticulous training and validation, the ANN demonstrates a remarkable 3% error rate in comparison to experimental results, underscoring its precision. The methodology extends beyond prediction, facilitating the optimization of implant surfaces for enhanced osseointegration. Experimental validation, including Atomic Force Microscopy and Molecular Cytotoxicity Tests, corroborates the accuracy of the ANN predictions. The study pioneers a transformative era in dental implantology, introducing a tailored and adaptable approach that bridges gaps in understanding the intricate interplay between surface modifications and biological responses. This work sets the stage for a paradigm shift in dental science, emphasizing precision, personalization, and elevated standards of care.

1. Introduction

Dental implantology stands at the forefront of modern dentistry, continually evolving to enhance the success and longevity of implant treatments. Dental implant surfaces play a pivotal role in determining the success of implantation, influencing both mechanical and biological aspects (Li et al., 2023). The surface characteristics of dental implants play a pivotal role in dictating their osseointegration potential and overall biocompatibility (Sahrmann et al., 2017). Over the years, surface preparation methods for dental implant fixtures have undergone profound evolution, driven by the relentless pursuit of enhanced biocompatibility, rapid osseointegration, and reduced risk of peri-implantitis (Weidenbacher et al., 2017). These techniques are devised to reshape the implant's surface topography, alter its chemical composition, and fine-tune its energy properties, all in pursuit of optimizing its interaction with the surrounding bone tissue and soft structures (Van Oirschot et al., 2022). Sandblasting, for instance, harnesses abrasive particles to create micro- and nano-scale irregularities, rendering the implant surface amenable to mechanical interlocking with the bone. Simultaneously, acid etching employs chemical agents like hydrochloric acid to modify surface chemistry, cleansing it of impurities, oxides, and foreign substances, thus rendering it more receptive to cell adhesion and tissue integration (Yavari et al., 2014). The ingenious SLA method combines sandblasting with acid etching, yielding a textured surface that exceptionally encourages bone cell adhesion and proliferation. Anodizing, on the other hand, employs an electrochemical process to create an oxide layer on the implant's surface, typically using titanium as the foundational material (Ahmadi et al., 2014). This oxide layer bestows corrosion resistance, biocompatibility, and enhanced wettability upon the implant surface. The choice of the optimal surface preparation method hinges on several factors, including the type of implant, the quality of the recipient bone, and the desired clinical objectives (Jahanmard et al., 2020). As research persists, dental professionals and scientists continue to explore innovative surface modification techniques, further refining the performance of dental implant fixtures within the ever-advancing realm of dental

* Corresponding author.
E-mail addresses: bijan_mohammadi@iust.ac.ir bijanm@sdu.dk (B. Mohammadi)

ISSN 2291-8752 (Online) - ISSN 2291-8744 (Print)

doi: 10.5267/j.esm.2024.12.003

science (Belluomo et al., 2023). Among the various surface modification techniques, the SLA+Anodizing method has gained prominence for its ability to optimize implant surfaces, offering improved mechanical and biological properties (Cecotto et al., 2023). This method involves a coupled treatment of Sandblasting, Large-grit, Acid-etching (SLA), and Anodizing, aiming to optimize the surface properties for improved osseointegration. The success of dental implants relies on their ability to integrate seamlessly with the surrounding bone tissue (Khodaei et al., 2022). Surface modifications aim to create an environment conducive to osseointegration, where the implant fuses with the bone, ensuring stability and functionality. The SLA+Anodizing method combines Sandblasting, Large-grit, Acid-etching (SLA), and anodizing to enhance the surface topography and composition (Mohammadi & Anbarzadeh , 2022). This method has shown promise in promoting faster osseointegration and improved biomechanical performance. Surface roughness is a critical parameter influencing the interaction between implants and biological tissues. It directly affects cellular response, protein adsorption, and the formation of the bone-implant interface (Garabetyan et al., 2019). Accurate assessment and prediction of roughness parameters are imperative for designing implants with optimal biocompatibility. In this context, the integration of artificial neural networks (ANNs) as a predictive tool holds significant promise (Koo et al., 2019). The complexity of relationships between surface characteristics and cellular responses necessitates advanced computational models. ANNs, inspired by the human brain's neural structure, provide a powerful tool for modeling intricate patterns within datasets (Costa-Berenguer et al., 2018). Leveraging ANNs in dental implant research allows for the development of predictive models capable of forecasting roughness parameters and cellular viability with a high degree of accuracy (Chi et al., 2021). ANNs offer a robust framework for modeling complex relationships between various parameters, allowing for precise predictions of roughness characteristics. In this regard, researchers have conducted numerous studies in this field. In their 2015 study, Khanlou and et al laid the groundwork for predicting and characterizing surface roughness in titanium biomaterials. Building upon their work, the current research utilizes an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to forecast surface roughness in the context of sandblasting and acid etching processes (Khanlou et al., 2015). The experiment, conducted on Ti-13Zr-13Nb surfaces, explored variations in process parameters, such as time and temperature, employing sandblasted, large-grit, acid-etched (SLA) methodology. By integrating polishing, sandblasting, and acid etching, or SLA, subsequent modifications to surface properties were achieved. The use of alumina particles for surface blasting and Kroll's etchant in different conditions led to a reduction in surface roughness, particularly under high-temperature conditions. Notably, the ANFIS model demonstrated robust predictive capabilities, achieving a 10% error margin when forecasting the Ra value for textured surfaces. This research not only advances the understanding of surface modification techniques but also underscores the potential of ANFIS models in extracting biologically relevant information from roughened surfaces based on surface roughness. In their 2021 study, Altuğ and et al investigated the impact of heat treatment on the microstructural, mechanical, and conductivity characteristics of Ti6Al4V titanium alloy using wire electrical discharge machining (WEDM). Employing scanning electron microscope (SEM), optical microscope, and X-ray diffraction (XRD) examinations, they assessed various properties and conducted microhardness and conductivity measurements (Altuğ et al., 2015). Heat treatments induced micro-changes successfully, and the study employed an L18 Taguchi experimental design to analyze the effects on machinability via WEDM and post-processing surface roughness (Ra) values. Utilizing artificial neural network (ANN) optimization, the study achieved minimal surface roughness, and results from the response surface method aligned well with experimental findings. Tilebon et al. in 2022 thoroughly examined the acid-etching process for commercially pure titanium dental implants, exploring the influence of diverse conditions. Utilizing an innovative approach, they introduced three artificial neural networks to predict essential parameters like surface roughness (Ra), peak-to-valley height (Rz), and weight loss (WL) across varying etching times and temperatures. The models revealed a direct correlation, indicating that increased weight loss correlates with heightened surface roughness, transitioning from an initial 0.5 μm at WL = 0 to 2 μm at WL = 0.78 $\mu g/cm^2$. To optimize the process, the artificial neural network seamlessly integrated with a genetic algorithm (NSGA-II), adeptly forecasting and demonstrating optimal etching conditions (Sadati et al., 2015). This groundbreaking research offers valuable insights into the intricacies of acid-etching for titanium dental implants, opening avenues for further advancements in optimizing these crucial procedures. In 2023, Mohammadi et al. conducted several research studies examining dental implant surfaces through experimental, simulation, and numerical approaches (Anbarzadeh & Mohammadi, 2023). One notable aspect of their work was the scrutiny of dental implant fatigue and the treatment of surfaces using a method known as SLA+Anodizing. The outcomes of their research yielded optimal models for surface treatment, demonstrating that the SLA+Anodizing technique accelerates the implant treatment process compared to other experimental methods (Anbarzadeh & Mohammadi, 2023). This advancement suggests potential improvements in the efficiency of dental implant procedures, contributing valuable insights to the field. This pioneering study offers valuable insights into the complexities of sandblasting, acid etching, and anodizing techniques for titanium dental implants (Anbarzadeh & Mohammadi, 2023). It paves the way for further advancements in optimizing these crucial treatments (Mohammadi et al., 2021). In the present study, this research aims to develop a comprehensive artificial neural network-based tool for predicting surface roughness parameters and cellular viability on dental implant fixtures treated with the SLA+Anodizing method. Through this integration, we aim to gain a comprehensive understanding of diverse surface preparation scenarios in dental implantology. This approach allows us to customize implant surfaces to meet individual patient needs and conditions, improving the likelihood of successful and long-lasting implant procedures. By amalgamating advanced computational techniques with dental implantology, the study aims to bridge the existing gaps in understanding the intricate interplay between surface modifications and biological responses. This study introduces an innovative approach by leveraging artificial neural networks (ANNs) to develop a predictive tool. This effort leads to a new era in dental implantology characterized by precision, personalization, and elevated standards of care, where patient satisfaction and clinical outcomes harmoniously redefine the field.

2. Materials and research Methods

The success of osseointegration in dental implants is significantly influenced by the implant surface, which is impacted by various manufacturing processes, including machining, sandblasting, acid etching, and anodizing. The topography of the implant surface is crucial for both mechanical stability and cellular response. This study aims to enhance the quality of fixed implant surfaces through the SLA + Anodizing method by optimizing the surface treatment process. **Fig. 1**, illustrates the comprehensive process of fabricating and treating the surfaces of the dental implant fixtures used in this study.

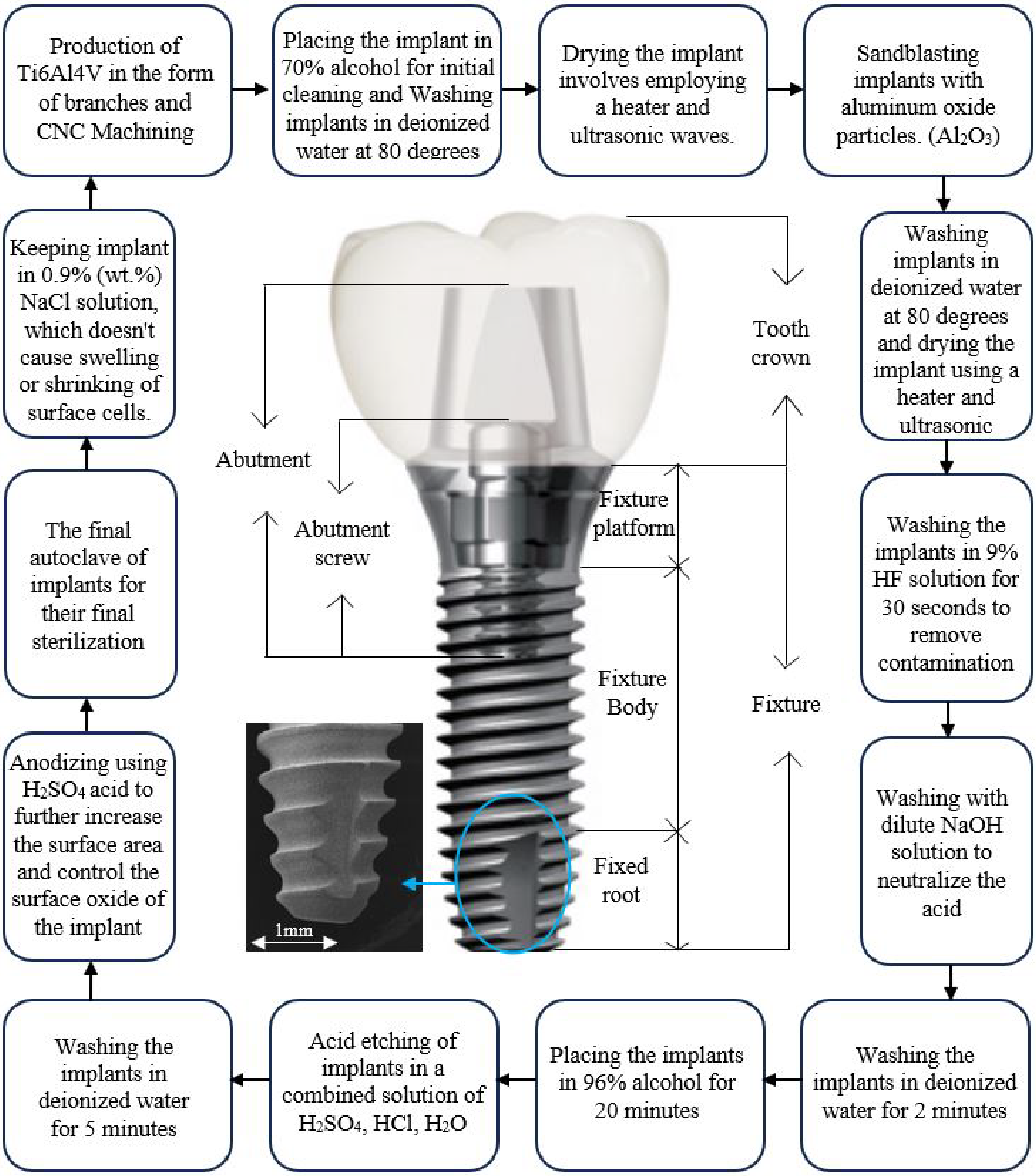


Fig. 1. The different stages of surface treatment of dental implant fixtures in this research

During the sandblasting process, aluminum oxide particles with dimensions of 75 micrometers were utilized under pressures ranging from 3 to 6 times and spraying angles between 30 to 50 degrees. Acid washing was conducted at ambient temperatures up to 75 degrees Celsius, lasting for 3 to 9 minutes, using a combination of sulfuric acid, hydrochloric acid, and water. Anodizing of the implants involved a sulfuric acid electrolyte solution for intervals ranging from 1 to 10 minutes, with voltage settings between 80 V to 120 V. The study explored various states of sandblasting, acid etching, and anodizing by manipulating these parameters. A total of 68 different conditions were examined, encompassing variations in sandblasting, etching, and anodizing parameters. In **Fig. 2**, a sample of implant treatment using the SLA+Anodizing method is illustrated with surface magnification at various scales.

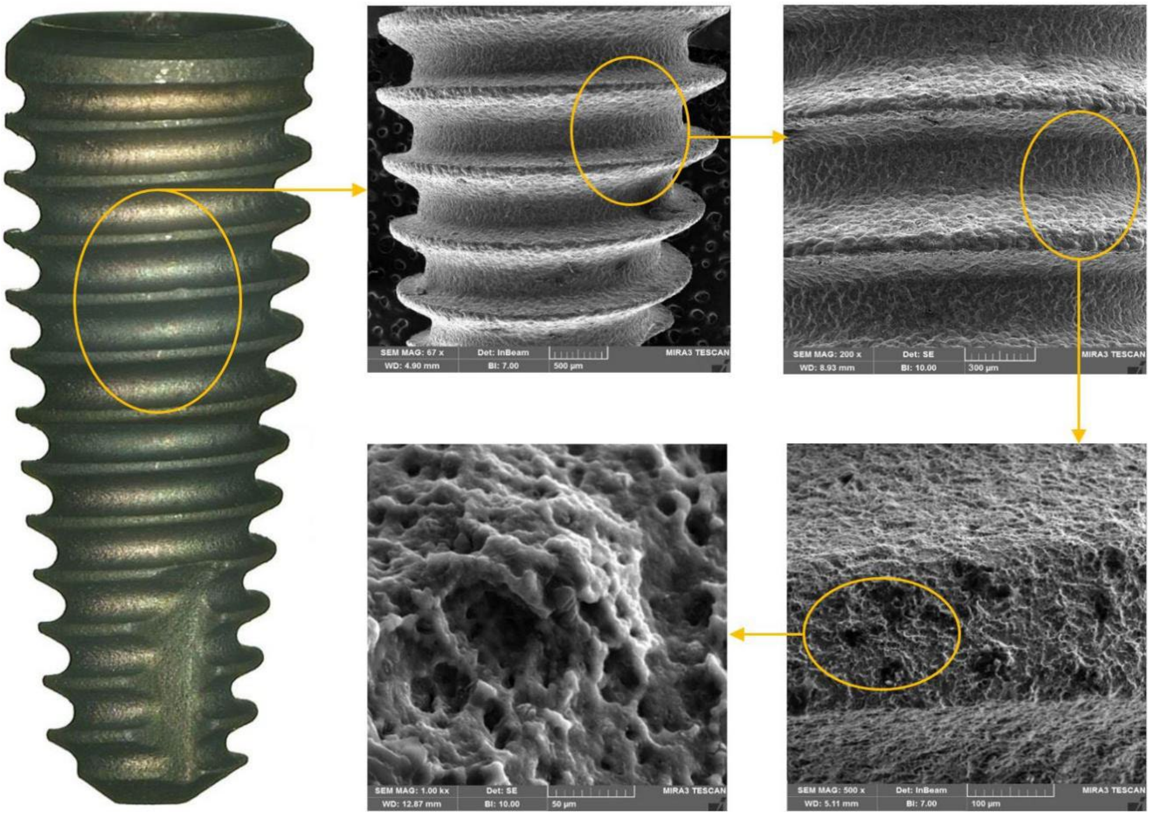


Fig. 2. FESEM images at various magnifications for an implant in the present study

3. Results

Recent studies have underscored the significance of appropriate surface roughness for the adhesion and proliferation of gingival osteoblastic cells. Surface roughness measurements were conducted using an atomic force microscope (AFM) due to its superior accuracy in characterizing small ridges (peaks) and depressions (valleys) on the surface compared to contact roughness measurement. Parameters quantifying surface roughness were assessed in both two dimensions (2D) and three dimensions (3D), with average roughness (Sa) being the most commonly used parameter, representing the average height of the profile. The standard surface roughness level for dental implant fixtures, based on well-known manufacturers such as Straumann, Megagen, Zimmer, and others, is approximately 2 microns with a tolerance of 0.2 microns (Park et al., 2013). AFM tests were conducted for all 68 surface preparation modes using the SLA+Anodizing method, and the average surface roughness results for each state were obtained in micrometers. Among the 68 cases, 26 exhibited average surface roughness close to the standard range associated with dental implant surfaces, leading to the initiation of the MTT test for these specific 26 cases. In studies involving cell and tissue culture, determining cell survival is crucial for assessing different substances and identifying chemical toxicity. The MTT method, a cytotoxicity test, measures cell death by quantifying the number of living cells through absorbance measurements at specific wavelengths. In this study, the surface of the 26 selected states from the AFM test was subjected to the MTT test, requiring three samples for each state. Experiments were conducted using a Memmert laboratory incubation device, and Lam-Neubar cells were counted among one hundred thousand cultured cells. The MTT method, relying on mitochondrial activity, involves color formation as an indicator of living cells. The absorption of solutes on the implant's hydrophilic surface occurs uniformly under favorable conditions. The mitochondrial activity, which remains stable in living cells, exhibits a linear correlation with the increase or decrease in the number of living cells. According to ISO10993-5, the standard rate of cell viability is set at 90% (Li et al., 2024). In the images obtained from the MTT test, white regions indicate cell viability, while gray or dark-colored rounded areas indicate cell death. Finally, as an example, the results of both AFM and MTT tests for three state numbers, 19, 39, and 59, out of the total 68 selected states, are presented in Fig. 3. The specifications of sandblasting, acid etching, and anodizing for all three states, 19, 39, and 59, are mentioned in Fig. 3. Subsequently, leveraging the comprehensive results from AFM and MTT tests, an Artificial Neural Network (ANN) was employed for training in this research. The ANN method initiated predictions for 65 out of the total 68 states, with information on states No. 28, 29, and 48 withheld until after the training. The accuracy of the ANN's predictive performance was then compared with the practical test results of these three states, providing valuable insights into the correlation between surface characteristics and cellular responses in the context of dental implant materials.

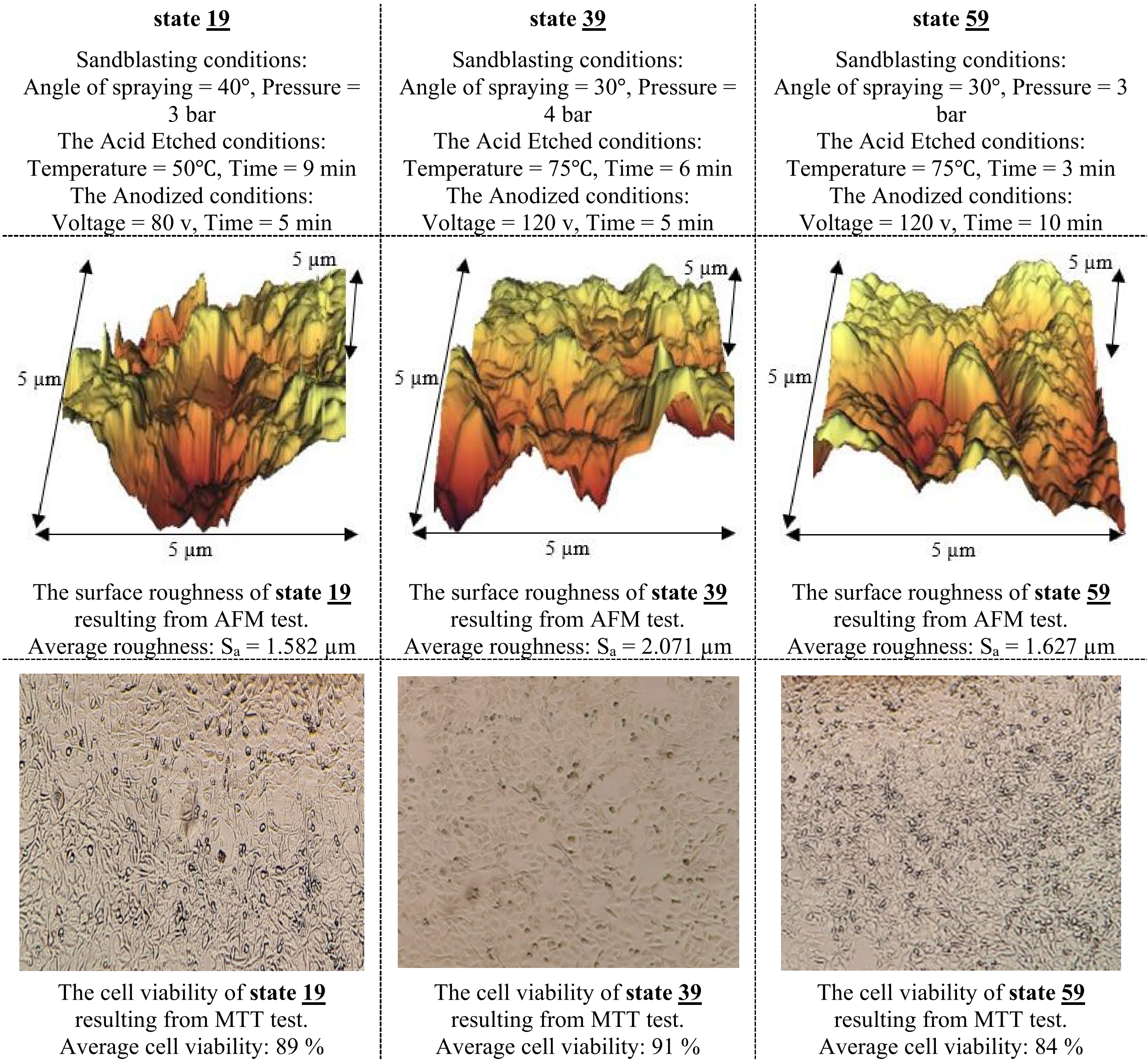
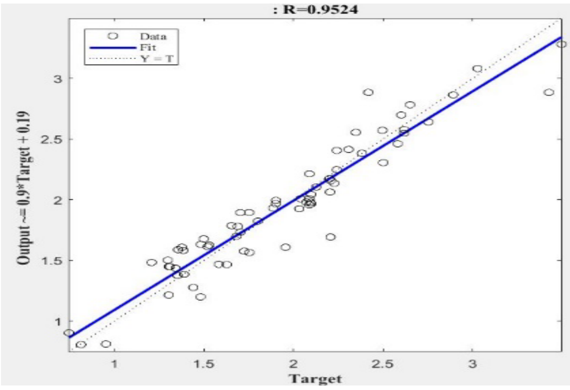
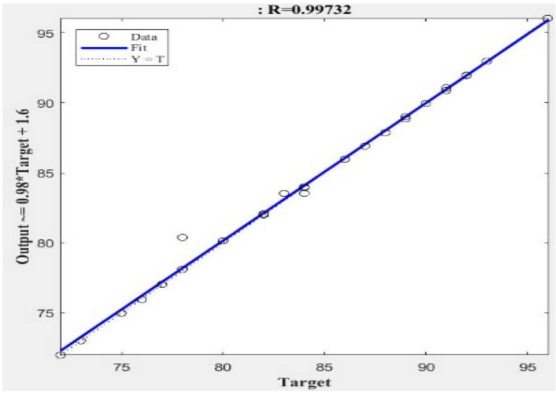


Fig. 3. The conditions of surface treatment (sandblasting, acid etching, and anodizing) and the results of surface roughness and cell viability obtained from AFM and MTT tests are related to three states, namely, 19, 39, and 59, which have been randomly selected from all 68 investigated states in this study.

The ANN was trained to provide regression predictions, and the outcomes are visually represented in **Fig. (4-a)**. According to **Fig. (4-b)**, the results of the average surface roughness for all 65 different states are presented, juxtaposed with the predicted outcomes of the ANN. Notably, the percentage difference between the predicted and experimentally obtained results is negligible, highlighting the high precision of the tests and the accurate coding of the artificial neural network. This underscores the method's self-correction capability in defining an appropriate and accurate pattern aligned with the experimental results. **Fig. 5**, further organizes the results from **Fig. (4-b)**, presenting them in ascending order of surface roughness. This provides a clear depiction of the progression of surface roughness for the 68 conducted states based on artificial intelligence testing and prediction.

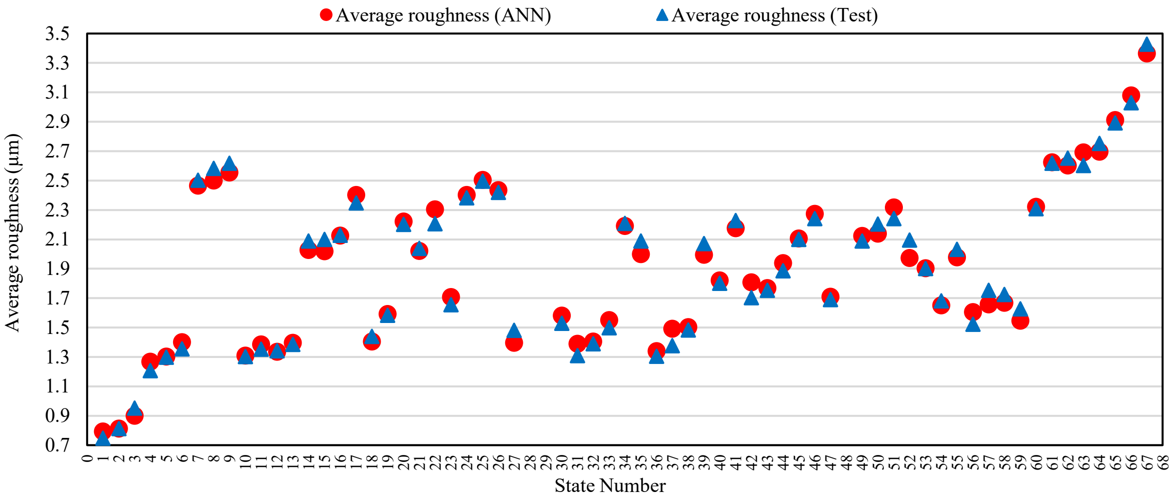


Regression analysis of the ANN related to surface roughness



Regression analysis of the ANN related to cell viability

a) Regression analysis results of the ANN compared to the tested results for various tested conditions.



b) Comparison of the predicted average surface roughness results by the ANN with the practical test results.

Fig. 4. Evaluating cell viability and surface roughness predictions using neural network regression

The comparison of average cell viability test results for 26 distinct conditions in this study with the predictions from artificial intelligence (AI) for cell viability is illustrated in **Fig. 6.**

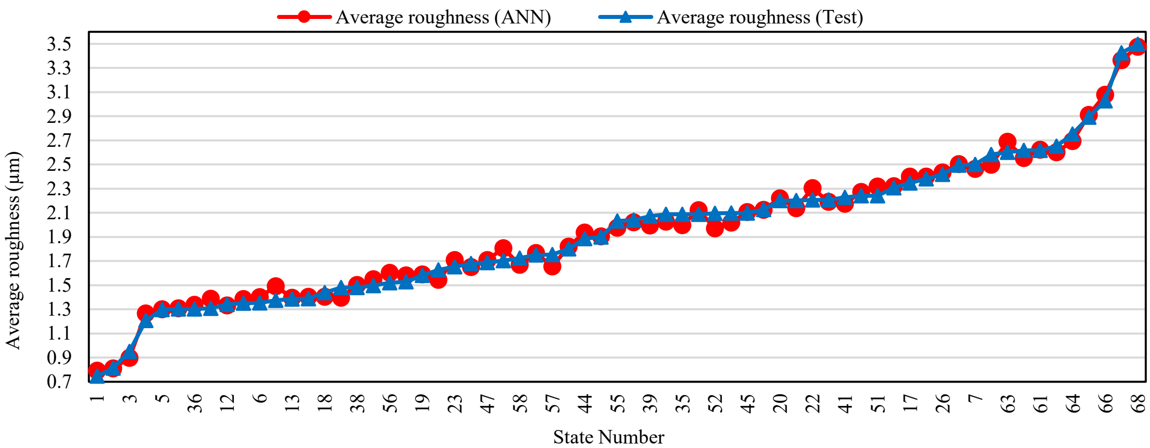


Fig. 5. The increasing trend of predicted average surface roughness results by the ANN compared to the practical test results.

Additionally, these outcomes are presented in ascending order, ranging from the lowest to the highest percentage of surface cell viability for these 26 cases, as depicted in **Fig. 7**. The conclusive findings reveal that cell survival rates for various state numbers, as determined by the practical tests in this research, closely align with the predictions made by artificial intelligence, with a minimal percentage difference. Furthermore, survival conditions that fell outside the standard range in the practical cell viability test were similarly identified and excluded in the artificial intelligence predictions.

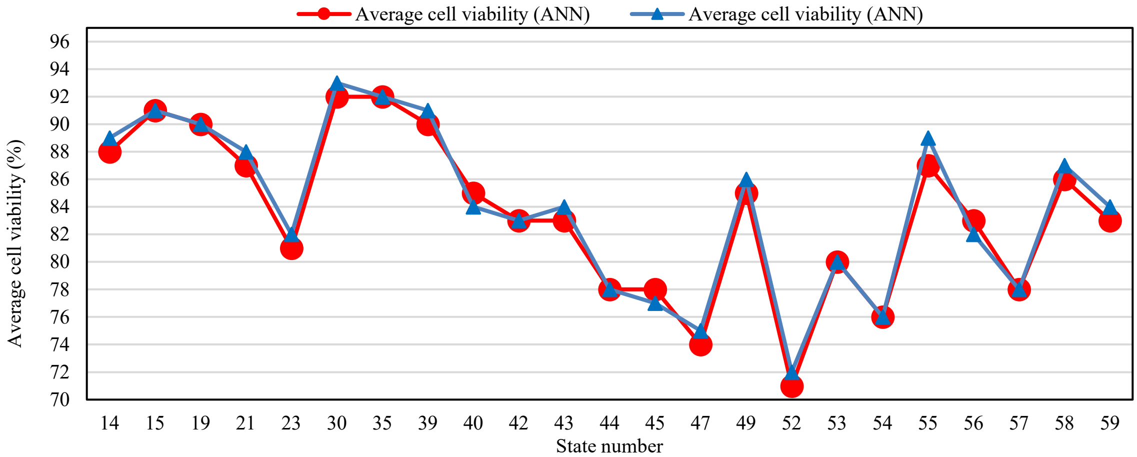


Fig. 6. Comparison of cell viability percentage results obtained from ANN predictions with the practical test results.

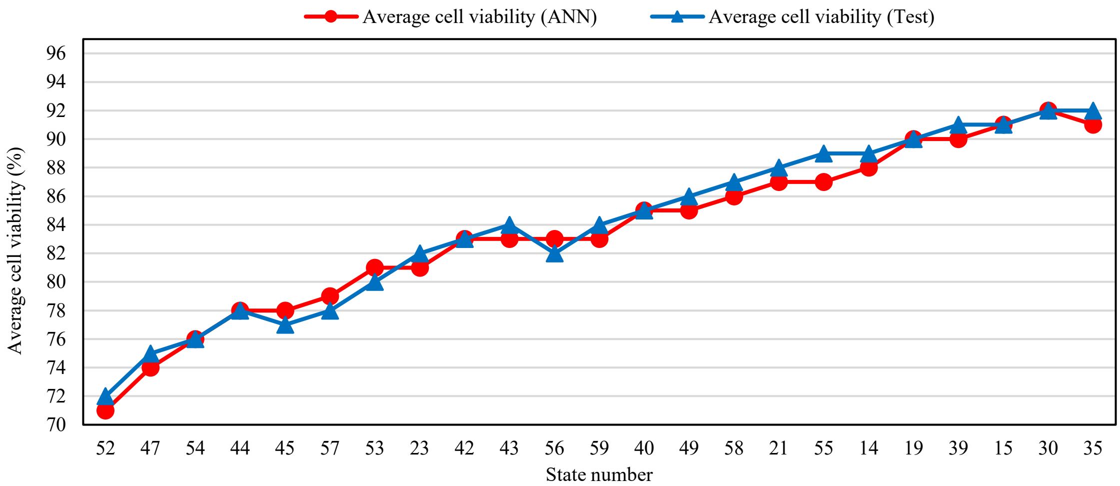
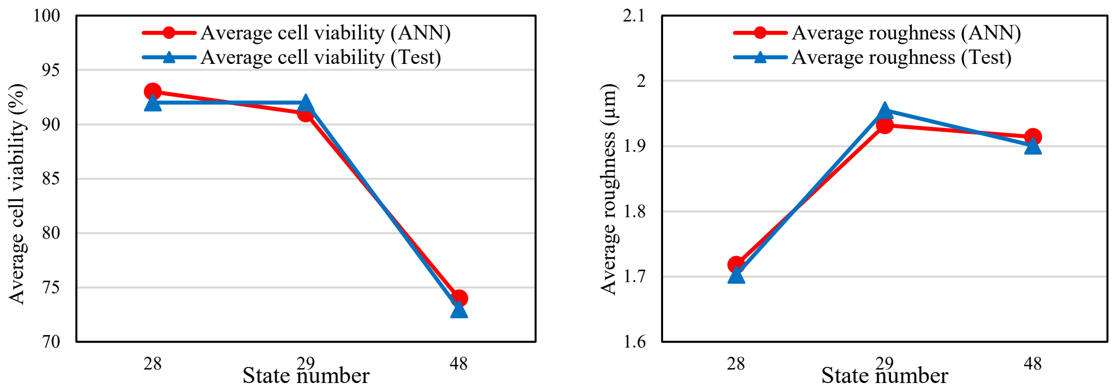


Fig. 7. The increasing trend of cell viability percentage results predicted by the ANN compared to the practical test results.

Finally, in **Fig. 8**, a comparison between the surface roughness and cellular viability results obtained from practical tests and the predictions of the ANN is presented for the three states: 12, 13, and 14. Notably, the information related to these states was intentionally withheld from the ANN during training, serving as a means to validate the accuracy of the network's performance. This examination is conducted to assess the precision and reliability of the software. According to the results in **Fig. 8**, the predicted outcomes of the ANN in the current study closely align with the practical test results, demonstrating a high level of accuracy.



Comparison of predicted cell viability results by the ANN with the test.

Comparison of predicted surface roughness results by the ANN with the test.

Fig. 8. Comparison of results obtained from practical testing and ANN predictions for cases where their information was not provided to the neural network in advance, to test the performance of the neural network through this comparison.

Now, considering the training of the ANN for the current research and the precise results obtained from the predictions of this statel, it is possible to achieve comprehensive outcomes for all surface roughness and cellular viability results, including cases not initially examined. This involves configuring the code to define various pressure and spraying angles, acid etching temperatures and times, as well as different voltages and times for anodizing, distinct from the initial 68 conditions. The ANN was tasked with predicting the results for surface roughness, cell viability percentage, and other desired outcomes across various blasting, acid etching, and anodizing parameters. This process involved a significantly larger number of cases, allowing for interpolation within the specified ranges of each variable. For the interpolation of different values of the relevant parameters, a set of cases was considered. In particular, a case with a blasting pressure of 4.5 bar, a spraying angle of 30 degrees, an acid etching temperature of 75 degrees Celsius, an acid etching time of 6 minutes, an anodizing voltage of 120 volts, and an anodizing time of 5 minutes demonstrated the best cell viability percentage at 93% and a surface roughness of 2.063 microns, falling within the standard range for dental implants. Similarly, for the extrapolation of values for various parameters, a case with a blasting pressure of 4.5 bar, a spraying angle of 20 degrees, an acid etching temperature of 80 degrees Celsius, an acid etching time of 6 minutes, an anodizing voltage of 120 volts, and an anodizing time of 5 minutes yielded the best cell viability percentage at 97% and a surface roughness of 2.069 microns, also falling within the standard range for dental implants. In Fig. 9, the outcomes of cell survival for two novel states, achieving 93% and 97% survival, were evaluated through MTT tests based on the interpolated (ANN-1) and extrapolated (ANN-2) predictions of the artificial neural network. The results of their respective survival tests were 91% and 94%. As anticipated, the state interpolated by the neural network (ANN-1) demonstrated a close match with the actual and practical test state, with only a slight error. On the other hand, the extrapolated state (ANN-2) exhibited a higher error of nearly 3%. Moreover, the surface roughness of these two states obtained from the AFM test is 2.069 and 2.036 micrometers. Fig. 9, illustrates a comparison of the average surface roughness and cell viability for these two surfaces with the selected state of the present study, i.e., state number 29. To investigate osteogenesis, a layer of bone cells (MG63 cells) was cultured on the surfaces of the implants.

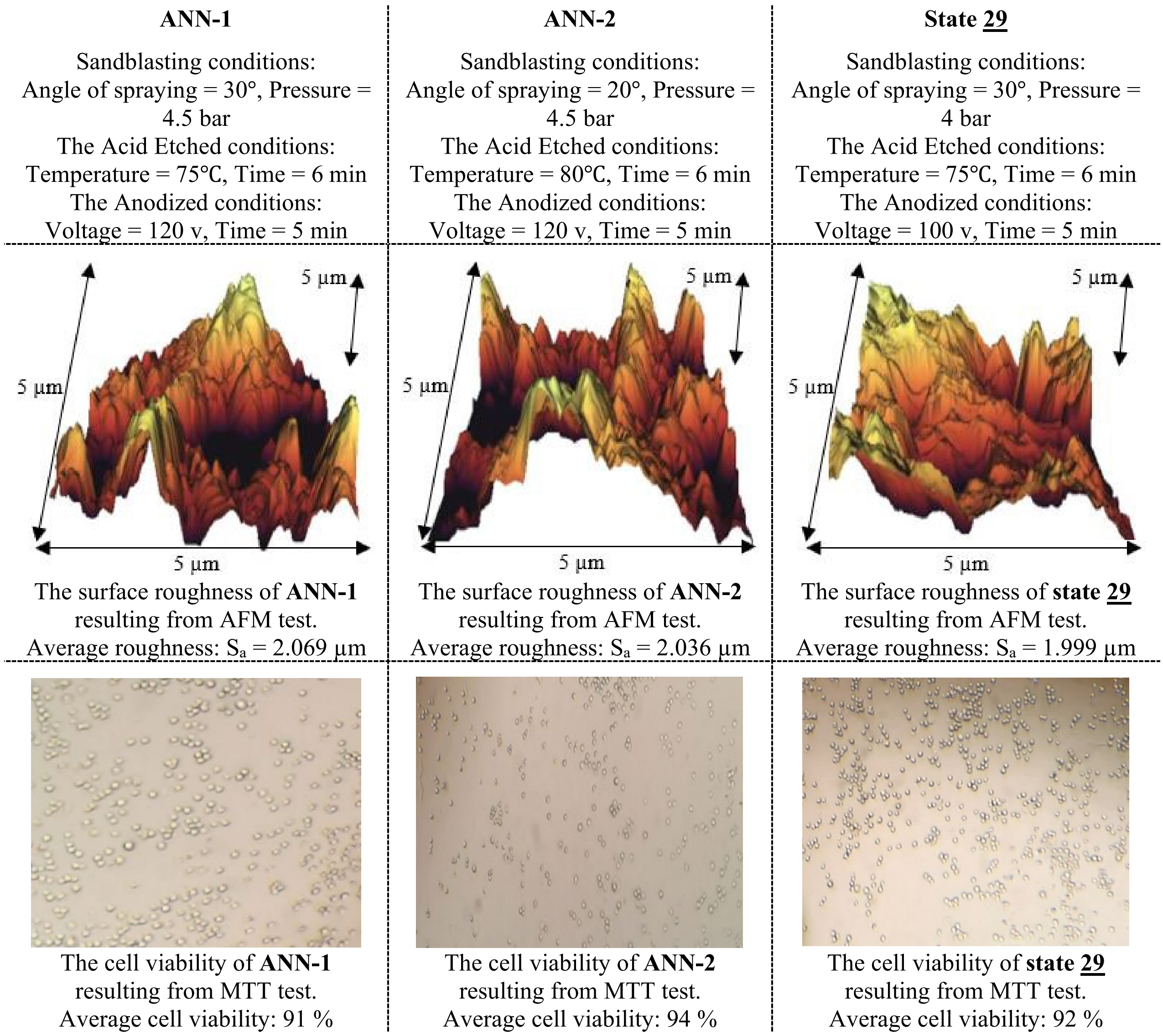
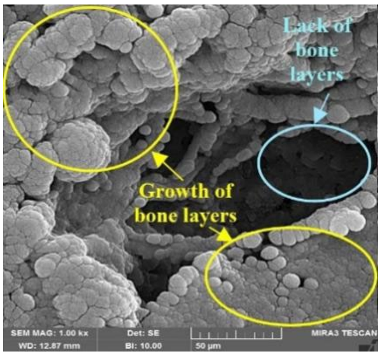
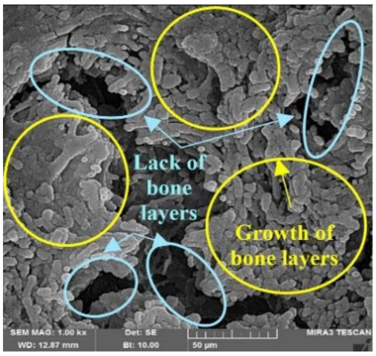


Fig. 9. Comparison of surface roughness and cell viability results for the interpolated and extrapolated states by the neural network with the selected state among all 68 investigated states in the present study.

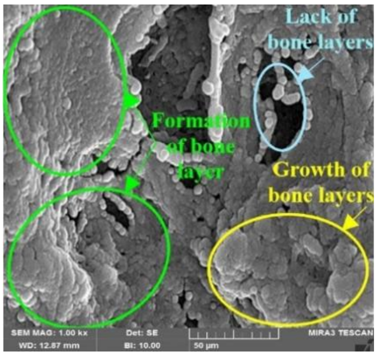
After culturing the bone layer on the fixture surfaces, FESEM microscopy was employed to capture images of the sample surfaces at three different time points (4, 8, and 12 days). This approach allowed for a visual and qualitative assessment of bone growth and the formation of a bone layer on the fixture surfaces over time. The results of the bone formation test for state 29 and two states obtained from the ANN (ANN-1 and ANN-2) are presented in **Fig. 10**, at various time intervals. From the FESEM images obtained at a scale of 50 micrometers, it is evident that day by day, the growth of bone cells and osteogenesis through bridges and bone connections, known as osseointegration, between the bone layer cells and the surface of the implant samples, has increased. The black areas in the images indicate the absence of bone formation and the lack of a connection between bone cells and the fixture surface, while the white areas in the images represent areas where osteogenesis has occurred with the implant surface. As observed in Fig. 10, the level of cell growth and the formation of connections and bridges on the surface (white areas) for the ANN-2 neural network state are noticeably higher compared to other states at different time intervals. After the successful cultivation of a bone layer on the surfaces of dental implant fixtures, the assessment of bone growth and layer formation over time was conducted using Field Emission Scanning Electron Microscopy (FESEM). The imaging process was carried out at three distinct time points: 4, 8, and 12 days, allowing for a detailed visual and qualitative analysis. The results of the bone formation test, focusing on state 29 and two states predicted by the Artificial Neural Network (ANN-2 and ANN-1), are depicted in **Fig. 10** across various time intervals.



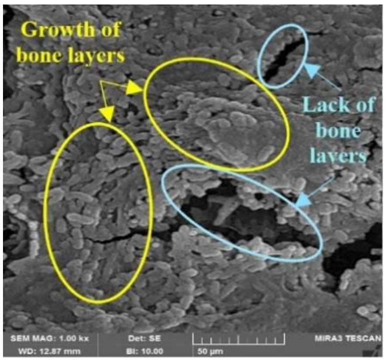
4 days post-osteogenesis process, state 29



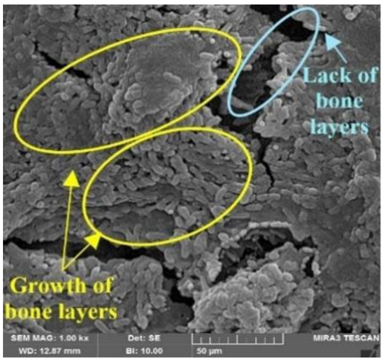
8 days post-osteogenesis process, state 29



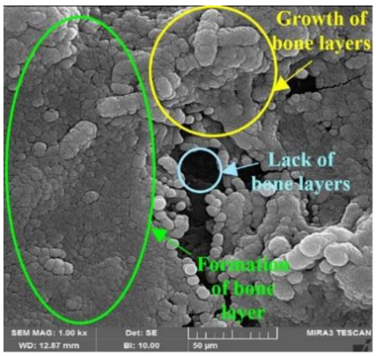
12 days post-osteogenesis process, state 29



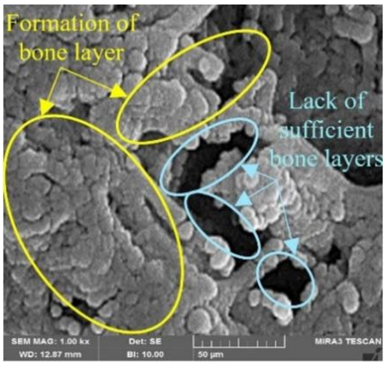
4 days post-osteogenesis of ANN-1 sample



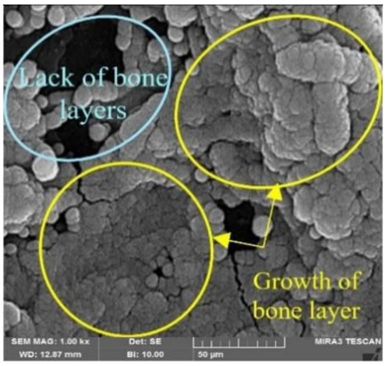
8 days post-osteogenesis of ANN-1 sample



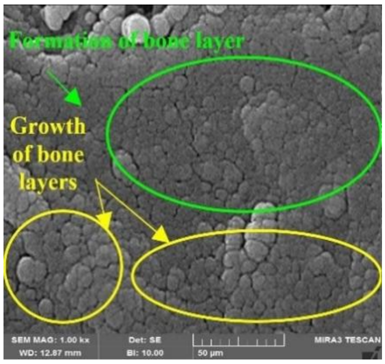
12 days post-osteogenesis of ANN-1 sample



4 days post-osteogenesis of ANN-2 sample



8 days post-osteogenesis of ANN-2 sample



12 days post-osteogenesis of ANN-2 sample

Fig. 10. The formation process of the bone layer on the surface of the selected sample in the current study (state 29) and two optimally selected states proposed by the artificial neural network (ANN).

FESEM images, acquired at a 50-micrometer scale, vividly illustrate the progressive development of bone cells and osteogenesis over consecutive days. This phenomenon is marked by the formation of bridges and connections, commonly known as osseointegration, between the bone layer cells and the surface of the implant samples. The black areas in the images signify the absence of bone formation and a lack of connection between bone cells and the fixture surface. In contrast, the white areas represent regions where successful osteogenesis has occurred on the implant surface. As evident in **Fig. 10**, the level of cell growth and the formation of connections and bridges (white areas) for the ANN-2 neural network state are significantly higher compared to other states at different time intervals. This observation underscores the efficacy of the Artificial Neural Network in predicting favorable conditions for osseointegration, providing valuable insights into the dynamics of bone formation and cellular interactions on treated dental implant surfaces. The ability to visually track and analyze these processes contributes to a deeper understanding of the success and integration of dental implants in clinical applications.

4. Discussion

This study aimed to optimize the surface treatment process for dental implants using the SLA + Anodizing method by exploring various combinations of sandblasting, acid etching, and anodizing parameters. An artificial neural network (ANN) was employed to predict surface roughness and cell viability based on these parameters. 68 different surface treatment conditions were investigated using AFM and MTT tests to assess surface roughness and cell viability, respectively. In this study, an extensive investigation was conducted into a diverse range of surface treatment parameters employing various analytical techniques. The successful utilization of Artificial Neural Networks (ANN) for the prediction of surface roughness and cell viability underscores its potential in optimizing surface treatment protocols. The validation of these predictions was carried out through in vitro bone growth assays. The study focused on in vitro testing, while clinical trials are needed to confirm the findings in real-world scenarios. The cost and resources required for extensive in vitro and clinical testing need to be considered for future research. Overall, this study highlights the potential of combining experimental approaches and artificial intelligence for optimizing dental implant surface treatment. Further research is needed to translate these findings into clinical practice and ensure the long-term success of dental implants.

5. Conclusion

This research endeavors to revolutionize dental implantology by introducing a novel predictive tool for estimating surface characteristics and cellular responses to various treatments using the SLA+Anodizing method. Leveraging an Artificial Neural Network (ANN), we trained the model with data from 68 distinct implant surface treatment states and validated its predictive capabilities against experimental tests. The results exhibited a remarkable congruence between ANN predictions and practical outcomes, with an error rate of approximately 3%. The study successfully demonstrated the potential of ANNs in predicting average surface roughness and cellular viability on dental implant surfaces. The accuracy of predictions was validated across diverse surface treatment scenarios, showcasing the adaptability and reliability of the developed tool. The integration of ANNs into dental implant research provides a sophisticated means to forecast complex relationships between surface parameters and cellular responses, enhancing the precision of predictions in comparison to traditional methods. Furthermore, the research expanded its scope by interpolating and extrapolating predictions for additional treatment scenarios. The ANN accurately predicted outcomes for novel states, demonstrating its robustness and effectiveness in scenarios not explicitly covered during training. This capability opens avenues for exploring a broader spectrum of treatment conditions and tailoring implant surfaces to individual patient needs. Experimental validation, including Atomic Force Microscopy (AFM) and Molecular Cytotoxicity Tests (MTT), reaffirmed the accuracy of ANN predictions. The comprehensive evaluation of surface roughness and cellular viability across diverse conditions provided insights into optimal treatment parameters for enhanced implant success. FESEM images further corroborated the positive impact of ANN-optimized states on bone layer formation and osseointegration. In conclusion, this study pioneers the application of ANNs in dental implantology, introducing a precise and versatile tool for predicting surface characteristics and cellular responses. The amalgamation of advanced computational techniques with dental science heralds a new era of personalized implant treatments, where patient-specific considerations guide the optimization of implant surfaces. This research contributes to the ongoing evolution of dental implant technologies, fostering improved patient outcomes and prolonged implant success.

Abbreviations

SLA: Sandblasted large grit acid etched

SLA+Anodizing: Sandblasted large grit acid etched + anodizing

ANN: Artificial neural network

AFM: Atomic force microscope

MTT: Molecular cytotoxicity Test

FESEM: Field emission scanning electron microscopy

Acknowledgments

The authors thank Dorin Kasht Mana Company, the largest manufacturer of dental implant systems in Iran, and especially Dr. Ali Asgar Malek Altojjari, the founder of the company, for providing information on the brand 3A.

References

Ahmadi, S.M., Campoli, G., Yavari, S.A., Sajadi, B., Wauthlé, R., Schrooten, J., Weinans, H., & Zadpoor, A.A. (2014). Mechanical behavior of regular open-cell porous biomaterials made of diamond lattice unit cells. *Journal of Mechanical Behavior of Biomedical Materials, 34*, 106-115. doi: 10.1016/j.jmbbm.2014.02.003

Altuğ, M., Erdem, M., Ozay, C., & Bozkır, O. (2022). Surface roughness of Ti6Al4V after heat treatment evaluated by artificial neural networks. *Materials Testing, 58*(2), 189-199. doi: 10.3139/120.110844

Anbarzadeh, E., & Mohammadi, B. (2023). Improving the surface roughness of dental implant fixtures by considering the size, angle, and spraying pressure of sandblast particles. *Journal of Bionic Engineering, 4*, 1-22. doi: 10.1007/s42235-023-00422-1

Anbarzadeh, E., & Mohammadi, B. (2023). Investigation of the effects of sandblasting, acid etching, and anodizing parameters in the SLA+ anodizing on the surface treatment of titanium dental implant fixtures. *Physics of Metals and Metallography, 29*, 1-4. doi: 10.1134/S0031918X23600793

Anbarzadeh, E., Mohammadi, B., & Azadzaeim, M. (2023). Effects of acid etching parameters on the surface of dental implant fixtures treated by proposed coupled SLA-anodizing process. *Journal of Materials Research, 38*(12), 4951-4966. doi: 10.1557/s43578-023-01205-4

Belluomo, R., Khodaei, A., & Yavari, S.A. (2023). Additively manufactured Bi-functionalized bioceramics for reconstruction of bone tumor defects. *Acta Biomaterialia, 156*, 234-249. doi: 10.1016/j.actbio.2022.08.042

Cecotto, L., Stapels, D.A., van Kessel, K.P., Croes, M., Lourens, Z., Vogely, H.C., van der Wal, B.C., Van Strijp, J.A., Weinans, H., & Yavari, S.A. (2023). Evaluation of silver bio-functionality in a multicellular in vitro model: towards reduced animal usage in implant-associated infection research. *Frontiers in Cellular and Infection Microbiology, 13*, 1186936. doi: 10.3389/fcimb.2023.1186936

Chi, Y., An, S., Xu, Y., Liu, M., & Zhang, J. (2021). In vitro biocompatibility of a sandblasted, acid-etched HA composite coating on ultrafine-grained titanium. *RSC Advances, 11*(9), 6124-6130. doi: 10.1039/D0RA10146J

Costa-Berenguer, X., García-García, M., Sánchez-Torres, A., Sanz-Alonso, M., Figueiredo, R., & Valmaseda-Castellón, E. (2018). Effect of implantoplasty on fracture resistance and surface roughness of standard diameter dental implants. *Clinical Oral Implants Research, 29*(1), 46-54. doi: 10.1111/clr.13037

Garabetyan, J., Malet, J., Kerner, S., Detzen, L., Carra, M.C., & Bouchard, P. (2019). The relationship between dental implant papilla and dental implant mucosa around single-tooth implant in the esthetic area: A retrospective study. *Clinical Oral Implants Research, 30*(12), 1229-1237. Doi: 10.1111/clr.13536

Jahanmard, F., Dijkmans, F.M., Majed, A., Vogely, H.C., Van Der Wal, B.C., Stapels, D.A., Ahmadi, S.M., Vermonden, T., & Yavari, S.A. (2020). Toward antibacterial coatings for personalized implants. *ACS Biomaterials Science & Engineering, 6*(10), 5486-5492. doi: 10.1021/acsbiomaterials.0c00683

Khanlou, H.M., Ang, B.C., Barzani, M.M., Silakhori, M., & Talebian, S. (2015). Prediction and characterization of surface roughness using sandblasting and acid etching process on new non-toxic titanium biomaterial: adaptive-network-based fuzzy inference system. *Neural Computing and Applications, 26*(7), 1751-1761. doi: 10.1007/s00521-015-1833-z

Khodaei, A., Jahanmard, F., Hosseini, H.M., Bagheri, R., Dabbagh, A., Weinans, H., & Yavari, S.A. (2022). Controlled temperature-mediated curcumin release from magneto-thermal nanocarriers to kill bone tumors. *Bioactive Materials, 11*, 107-117. 10.1016/j.bioactmat.2021.09.028

Koo, K.T., Khoury, F., Keeve, P.L., Schwarz, F., Ramanauskaite, A., Sculean, A., & Romanos, G. (2019). Implant surface decontamination by surgical treatment of periimplantitis: A literature review. *Implant Dentistry, 28*(2), 173-176. Doi: 10.1097/ID.0000000000000840

Li, J., Qin, W., Osei Lartey, P., Fu, Y., & Ma, J. (2023). Hydrothermal desulfurization on porous sulfonated CFR-PEEK surface structure used for implant application. *Journal of Bionic Engineering, 20*(3), 748-761. doi: 10.1007/s42235-022-00276-z

Li, Y., Liu, X., Wang, F., Zhou, W., & Ren, X. (2024). Influence of ultrasonic shot peening on the surface acid etching behavior of pure titanium. *Materials Chemistry and Physics, 313*, 128720. doi: 10.1016/j.matchemphys.2023.128720

Mohammadi, B., & Anbarzadeh, E. (2022). Evaluation of viability and cell proliferation in bone and gingival on dental implant fixtures with active sandblasted and sandblasted surfaces by the cytotoxicity test method. *Journal of Biomimetics, Biomaterials and Biomedical Engineering, 56*, 165-172. doi: 10.4028/p-gmmc8m

Mohammadi, B., Abdoli, Z., & Anbarzadeh, E. (2021). Investigation of the effect of abutment angle tolerance on the stress created in the fixture and screw in dental implants using finite element analysis. *Journal of Biomimetics, Biomaterials and Biomedical Engineering, 51*, 63-76. doi: 10.4028/www.scientific.net/JBBBE.51.63

Park, J.B., Jang, Y.J., Koh, M., Choi, B.K., Kim, K.K., & Ko, Y. (2013). In vitro analysis of the efficacy of ultrasonic scalers and a toothbrush for removing bacteria from resorbable blast material titanium disks. *Journal of Periodontology, 84*(8), 1191-1198. doi: 10.1902/jop.2012.120369

Sadati Tilebon, S.M., Emamian, S.A., Ramezanpour, H., Yousefi, H., Özcan, M., Naghib, S.M., Zare, Y., & Rhee, K.Y. (2022). Intelligent modeling and optimization of titanium surface etching for dental implant application. *Scientific Reports, 12*, 7184. doi: 10.1038/s41598-022-11254-0

Sahrmann, P., Schoen, P., Naenni, N., Jung, R.E., Attin, T., & Schmidlin, P.R. (2017). Peri-implant bone density around implants of different lengths: A 3-year follow-up of a randomized clinical trial. *Journal of Clinical Periodontology, 44*(7), 762-768. doi: 10.1111/prd.12577

Van Oirschot, B.A., Zhang, Y., Alghamdi, H.S., Cordeiro, J.M., Nagay, B.E., Barao, V.A., De Avila, E.D., & Van Den Beucken, J.J. (2022). Surface engineering for dental implantology: favoring tissue responses along the implant. *Tissue Engineering Part A, 28*(5), 555-572. doi: 10.1089/ten.tea.2021.0230

Weidenbacher, L., Abrishamkar, A., Rottmar, M., Guex, A.G., Maniura-Weber, K., deMello, A.J., Ferguson, S.J., Rossi, R.M., & Fortunato, G. (2017). Electrospraying of microfluidic encapsulated cells for the fabrication of cell-laden electrospun hybrid tissue constructs. *Acta Biomaterialia, 64*, 137-147. Doi: 10.1016/j.actbio.2017.10.012

Yavari, S.A., van der Stok, J., Chai, Y.C., Wauthle, R., Birgani, Z.T., Habibovic, P., Mulier, M., Schrooten, J., Weinans, H., & Zadpoor, A.A. (2014). Bone regeneration performance of surface-treated porous titanium. *Biomaterials, 35*(22), 6172-6181. Doi: 10.1016/j.biomaterials.2014.04.054