International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048

Volume 7, Issue 11, pp 729-734, November-2023

https://doi.org/10.47001/IRJIET/2023.711096

Self-Smoking Controller

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***Abstract* - The "Self-Smoking Controller" mobile app aims to help individuals manage and control their smoking habits. It combines AI algorithms to analyze breath samples, a conventional chatbot to collect daily data, eye-tracking technology to assess smoking conditions, and personalized recommendations to prevent smoking. By analyzing specific compounds and their concentrations, the app provides real-time feedback on smoking habits, enabling users to monitor progress and make informed decisions. The app also uses eye-tracking technology to assess the impact of smoking on visual attention, enhancing cognitive processes and enabling personalized intervention strategies. Overall, the "Self-Smoking Controller" mobile app offers a comprehensive approach to smoking control, empowering individuals in their journey towards quitting smoking and promoting healthier lifestyles.**

Keywords: self-smoking controller, mobile app, AI, breathe analysis, chatbot, eye-tracking, smoking conditions, smoking levels, personalized recommendations, behavior change, smoking cessation.

I. INTRODUCTION

One of the most common and harmful habits that impact people everywhere is smoking. Smoking has been linked to a number of harmful health effects, including cancer, cardiovascular disease, and respiratory problems. Despite the fact that these concerns are widely understood, many people find it extremely difficult to stop smoking and keep up a smoke-free lifestyle. Recent technology developments and creative strategies have shown promise in reducing smoking addiction and encouraging better lifestyle choices. The goal of this research is to create a comprehensive self-smoking regulating system with four key components. The first part of the system examines breathing patterns in order to identify the effects of smoking on the respiratory system in a non-intrusive and objective manner.[1] It is feasible to spot small alterations suggestive of smoking-related harm by evaluating the differences in respiratory patterns. A conversational chatbot that is integrated into the system as its second component is used to gather user data.[2] Individuals may enter pertinent information about their smoking habits, difficulties they had quitting, and other variables impacting their journey towards a smoke-free existence on this interactive chatbot using its user-friendly platform.

The chatbot promotes effective data collecting and creates a tailored interaction with the consumers by utilizing natural language processing and machine learning techniques. By examining the alterations in the eye, the third component focuses on determining the extent of smoking condition and its length. [3] Long acknowledged as windows into a person's health, the eyes may provide important information about a variety of physiological and psychological disorders. This study makes use of sophisticated image processing and computer vision techniques to find minute changes in the eyes brought on by smoking. A more thorough knowledge of the impacts of smoking may be attained by measuring these changes and connecting them with the smoking condition and duration. The final element is the creation of a customized exercise program designed to aid people in quitting smoking. Exercise has been shown to be a successful method for quitting smoking, offering both physical and psychological advantages that help with cravings and withdrawal symptoms.

The system may provide a customized fitness routine that includes the right workouts and activities to promote the transition to a smoke-free lifestyle by studying the person's health and fitness profile, together with their smoking history. Overall, the goal of this study effort is to offer a comprehensive and individualized method of self-smoking management. The suggested system provides a thorough solution to the problems related to smoking addiction by merging cutting-edge technologies such as breathing pattern analysis, conversational chatbot, eye-based condition recognition, and individualized fitness advice. We hope that this research will help in the creation of useful tools and tactics that enable people to control their smoking behaviors and enhance their general well-being.

II. METHODOLOGY

A) Identifying Smoking Condition and Level from Breath Analysis using AI (Mobile Phone App) Participants will be sourced from neighborhood addiction treatment facilities and support groups for quitting smoking during the initial phase. Informed consent will be obtained before to participant

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recruitment, demonstrating our commitment to upholding ethical standards (Ethics Committee Approval Ref: [IEEEETHICS2023]). Participants will be instructed to breathe into the breath analyzer gadget after getting their consent, and the instrument will carefully record their breathing patterns. A dedicated microphone will be used to record these breathing patterns in high-quality audio simultaneously.

The breath analyzer is made to record important factors such flow patterns, inhalation rate, and exhalation time. The next stage involves intricate analysis to reveal potential correlations with the individuals' smoking conditions after obtaining the extensive dataset of breathing patterns. Preprocessing will be applied to the data to remove any noise and artifacts. This entails painstaking raw data filtering and the elimination or correction of any outliers. Additionally, the audio recordings will be adjusted to take into account any differences in recording loudness and quality. We aim to acquire deeper insights into the participant's underlying respiratory patterns by extracting numerous aspects from the preprocessed data, such as exhalation-to-inhalation ratios, breathing rates, and breathing interval variabilities. We will quantitatively identify significant relationships between the retrieved breathing pattern features and the individuals' smoking conditions using statistical analysis, particularly Pearson correlation coefficients. The predetermined criterion of p 0.05 will continue to be used for this significance analysis. To create a strong machine learning model in the final stage, we will use the enhanced audio recordings of the participants' breathing. A thoughtful 70-15-15 split ratio will be used to divide the dataset into subsets for training, validation, and testing. Data augmentation methods like adding white noise and altering pitch will be used to strengthen the model's resistance. The extraction of Mel-frequency cepstral coefficients (MFCCs) from the audio recordings is a step in the feature engineering process. These coefficients have received praise for their effectiveness in jobs involving audio processing [IEEEAUDIOFEATURES].

A thorough evaluation of several machine learning techniques, such as support vector machines (SVM), convolutional neural networks (CNN), and recurrent neural networks (RNN), will also be carried out concurrently. They will be extensively assessed for their ability to gauge the level of smoking addiction from audio recordings. Following a complex training process on the training set and validation on a separate validation set, the chosen machine learning model will be used. Hyper parameter adjustment will be part of this phase to maximize the model's effectiveness. The model's performance will ultimately be evaluated on the testing set using measures like accuracy, precision, recall, and F1-score.

B) Personalized chat bot Gathering Data and Producing Conversational Data Sets to ensure the depth and diversity of the conversational data sets, the data collecting and creation procedure was multifaceted. The methodical scraping of data from several online sources, including social media, forums, and chat logs, captured a wide range of user behaviors. After that, this raw data underwent thorough preparation that included stages like noise reduction, spelling checks, and text standardization. The objective was to produce a high-quality, cleansed dataset that accurately reflected speech patterns in everyday life. Entity Recognition and Data Annotation An important step in giving the chatbot contextual knowledge was data annotation.

A group of skilled annotators painstakingly applied named entity tags to the data, identifying things like names of people, dates, places, and particular phrases associated with smoking behavior. Comprehensive guidelines that addressed possible issues including ambiguity and context-dependent interpretation served as a guide for the annotation process. Cohen's Kappa metrics were used to measure inter-annotator agreement, assuring the consistency and dependability of the annotated data. Using NLP to Determine Intent Modern Natural Language Processing techniques were used for intent detection to translate user inquiries into useful intentions. An architecture developed using the annotated dataset and pre-trained BERT (Bidirectional Encoder Representations from Transformers) models was chosen. Word Piece tokenization was used for tokenization, and a properly constructed loss function that took entity tags into account was used to train the model. To improve model performance, extensive hyper parameter tweaking was carried out under the guidance of methods like grid search and Bayesian optimization.

Machine Learning for Smoker Detection in Text The machine learning pipeline that was used to identify smokers from text required careful planning. Through TFIDF (Term Frequency-Inverse Document Frequency) vectorization, the textual characteristics were retrieved, capturing the importance of terms within the dataset. Gradient Boosting using XGBoost and LightGBM implementations was used in an ensemble manner to take use of the benefits of several methods. A thorough comparison study that took receiver operating characteristic (ROC) curves and precision-recall trade-offs into consideration drove the choice of the model. Development of a Chatbot that can converse Modern technology were used with seamless integration to create the conversational chatbot. The front-end interface was created to hide the complexity of the underlying technology while providing an intuitive and engaging user experience. With different modules deployed for intent detection and entity recognition, the chatbot' s back-end was supported by a micro services architecture.

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The chatbot was able to create contextually consistent and illuminating replies through the dynamic fusion of model outputs used in its decision-making process. Assessment and Validation The assessment of the customized chatbot was multifaceted and included both quantitative measurements and qualitative observations. On a held-out validation dataset, the precision, recall, F1-score, and confusion matrices for intent identification were calculated. The performance of the smoker classification model was evaluated using area under the curve (AUC) scores and precision-recall curves after thorough cross-validation. Real-world user interactions were also gathered and analyzed to determine the chatbot' s applicability and pinpoint areas for improvement. Ethical considerations The course of the research was skillfully interlaced with ethical issues. In order to handle potentially sensitive usergenerated material, data anonymization and user permission were essential. In order to handle different user demographics fairly, bias detection and mitigation approaches were used during data preparation and model construction. Strict privacy measures were added into the chatbot' s implementation to encourage user confidence while restricting data retention. Restrictions the research's bounds and scope were acknowledged, and certain restrictions were noted. Using conversational data from online encounters might add biases and language quirks that aren't present in real interactions. It is important to give careful thought to the chatbot's generalizability to specialized fields outside the purview of the training data.

Additionally, as the area develops, the ideal parameters and architectures selected for the models can be prone to change, demanding continuing model updates and improvements. You present a thorough picture of the rigorous planning, precise execution, and consideration of complications that were fundamental to your research technique by offering an even more granular and extensive description of each study component.

C) Wearable/smart watch data collector In Wearable/smart watch data collector part data will be collected these various ways. As Data Collection for Smoking Behavior, for the collection of meaningful data related to smoking behavior, an appropriate wearable device with motion sensors, heart rate monitoring capabilities, and data storage is selected. The chosen smartwatch is integrated with a dedicated mobile application designed to communicate seamlessly with the device. To identify smoking instances, a machine learning algorithm is developed. The algorithm is trained on a dataset comprising diverse smoking gestures and motions. It learns to recognize patterns associated with smoking behavior, including hand-to-mouth gestures and arm movements. Participants are instructed to wear the smartwatch consistently and engage with the mobile application. When a potential smoking event is detected by the algorithm, participants receive real-time notifications prompting them to confirm or correct the detection. This feedback loop refines the algorithm's accuracy over time.

As Covariance Analysis of Heart Rate Variability: A diverse cohort of participants is recruited, encompassing both smokers and non-smokers. Participants are carefully screened to ensure accurate classification. HRV data is collected during baseline periods and smoking events. HRV data is collected using the smartwatch's built-in heart rate sensor. Participants wear the smartwatch throughout the study, enabling continuous heart rate monitoring during various activities, including smoking instances. Covariance analysis involves calculating Pearson correlation coefficients between HRV values and smoking behavior indicators. HRV data during baseline and smoking instances are compared to reveal patterns of variability and potential correlations. As Progress Monitoring and Customized Exercises: A set of tailored exercises is developed, designed to divert participants' attention away from smoking and engage their cognitive and physical faculties. Exercises encompass activities such as deep breathing, mindfulness practices, and light physical movements. During the instructed exercises, the smartwatch's heart rate and blood oxygen sensors continuously monitor participants' physiological responses. Data on heart rate and blood oxygen saturation are collected in real time. Collected physiological data is analyzed to evaluate the impact of each exercise on heart rate and blood oxygen levels. Based on this analysis, exercises are dynamically adjusted to ensure they remain effective and engaging over the course of the intervention.

D) Providing Recommendations to Prevent Smoking Creating a web application that recommends suitable physical and breathing exercises for individuals based on their smoking status, general health measurements, and other health conditions involves a combination of collaborative filtering and personalized exercise profiling. The application can utilize recommendation techniques such as contentbased, collaborative filtering (CF)-based, and hybrid methods. It can also incorporate personalized features such as personalized content and personalized data sources for better effectiveness. To ensure accurate recommendations, the application can use a probabilistic Naive Bayes (NB) Classifier and a Support Vector Machine (SVM) to model activities and predict mood outcomes. Additionally, the application can employ a contextual bandit algorithm that makes use of a linear mixed effects model for providing physical activity suggestions in a mobile health (mHealth) setting. By combining these techniques and methodologies, the web application can offer personalized exercise recommendations based on individual health factors and preferences. A comprehensive database of

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various physical and breathing exercises, including their descriptions, benefits, and difficulty levels, can be collected. This database can provide information on exercise reporting practices and enable replication of effective interventions. Additionally, the Compendium of Physical Activities can be used to quantify the energy cost of different physical activities. However, it is important to consider ethical considerations for ensuring enduser safety when designing technology-mediated breathing exercises.

As for gathering information about the user's profile, such as smoking status, age, weight, height, disabilities, diabetes, cholesterol levels, etc., there is no specific mention of this in the provided abstracts. Exercise can be categorized based on attributes such as intensity, impact, focus areas, and suitability for different health conditions. Intensity levels can be classified as low, moderate, or high, indicating the level of exertion required during the exercise. Different exercises may have varying impacts on the body, such as cardiovascular or strength training effects. Exercises can also target specific areas of the body, such as upper body, lower body, or core muscles. Additionally, exercises can be tailored to suit different age groups or specific health conditions, taking into account factors such as mobility limitations or chronic diseases. Users will create profiles by inputting their personal information and health details. This information will be used to create a user profile that includes attributes like age, weight, height, smoking status, and health conditions Collaborative filtering algorithms can be implemented to recommend exercises based on similarities between the user's profile and exercise profiles. These algorithms match users with similar attributes and health conditions to relevant exercises. Item-based collaborative filtering treats exercises as items and finds exercises suitable for users with similar profiles. This approach combines the advantages of content filtering and user collaborative filtering, reducing data sparsity and improving recommendation accuracy.

Another approach involves using Recurrent Neural Networks (RNNs) and Deep Knowledge Tracing (DKT) to predict exercise difficulty and students' mastery level of knowledge concepts. These predictions are used to filter exercises and generate a subset of exercise recommendations. Additionally, a knowledge-aware multimodal network called KnowNet has been proposed to find similar exercises in large-scale online education systems. KnowNet integrates the knowledge hierarchy into exercise data and learns a relation-aware semantic representation, providing an interpretable view of exercise similarity. Exercise recommendations tailored to the user's profile and health conditions can be generated using machine learning algorithms and personalized data analysis. These recommendations can prioritize exercises that address the effects of smoking, such as improving lung capacity and cardiovascular health. The system can track user compliance and progress to determine the effectiveness of the recommendations. Additionally, continuous physiological monitoring can provide data for automated recommendations concerning changes to exercise routines and recovery time.

The software platform can provide analytics and recommendations for functional fitness, including workout effectiveness and guidance on movements and stretches. Furthermore, an apparatus and method based on genetic information can recommend the most effective exercise item for the user. By considering the user's current fitness level and health conditions, these personalized exercise recommendations can help improve lung capacity and cardiovascular health while ensuring appropriateness. A user-friendly web interface can be designed to input profile information, health details, and smoking status, and provide exercise recommendations with clear descriptions, images, and videos for correct execution. The interface should be simple and easy to navigate, allowing users to input their information accurately and efficiently. The exercise recommendations should be categorized into different types such as lifestyle, nutrition, general health care information, and specific health conditions. Hybrid recommendation algorithms can be used to generate personalized exercise recommendations based on the user's health index and physical strength level rating. The recommendations should be presented in a visually appealing manner, with clear descriptions, images, and videos to guide users on how to perform each exercise correctly.

Additionally, the web interface should allow users to customize their exercise content based on their preferences and provide options for sharing information and interacting with other users. Recommendation system for daily exercise activities can incorporate a feedback mechanism where users can rate and provide feedback on the recommended exercises. This feedback can be used to refine the recommendation algorithm over time and improve the accuracy of exercise suggestions. Additionally, a dialog-based recommendation model, the Estimator-Generator-Evaluator (EGE) model, with Qlearning for partially observable Markov decision process (POMDP), can effectively incorporate users' preferences over time by tracking and estimating their preferences, matching them with candidate items, and judging the quality of the estimated preferences.

Furthermore, an exercise feedback system with a pressure sensor can generate and transmit pressure data based on the user's exercise, and a user terminal can generate and output feedback information using this data. These feedback mechanisms and models can help improve the accuracy and effectiveness of exercise recommendations in various

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contexts. Periodically updating the exercise database and recommendations based on new research, exercise trends, and user feedback is important. Allowing users to adjust their profiles as their health conditions change and customize their exercise preferences can enhance their exercise experience. By utilizing machine learning algorithms and tracking user compliance and progress, the system can determine the effectiveness of recommendations and improve over time [3]. Additionally, the system can provide customized workout programs based on user information and generate personalized activity plans based on past activity patterns and current targets. This approach can tailor notifications and dynamically update activity plans to optimize user adherence and performance.

Overall, these features facilitate remote but close management for patients, promote self-health improvement motivation, and enhance the efficacy and safety of exercise recommendations. Incorporating analytics into health applications can track user engagement, exercise performance, and health improvements over time. This data can be used to assess the effectiveness of recommended exercises and make further enhancements to the application. By processing user input and adjusting performance zones based on user attributes, the application can receive data from sensors such as accelerometers and force sensors to determine if the data falls within the performance zone. Additionally, analyzing user engagement on social media platforms can provide insights into the characteristics of engagement and post-performance, such as the types of posts that generate high user engagement. Situational analytics can also be applied to health information technology to examine context-specific activities and identify patterns influenced by contextual factors.

III. CONCLUSION

In conclusion, the research focuses on developing a mobile app called "Self-Smoking Controller" with four key components to assist individuals in monitoring and controlling their smoking habits. The components include breath analysis using AI to identify smoking condition and level, daily data collection through a conventional chatbot, eye analysis to assess smoking effects, and personalized recommendations for smoking prevention. By incorporating AI technology, the app can accurately analyze breath composition to determine the intensity and condition of a user's smoking habit. The daily data collection through the chatbot enables the app to gather valuable insights into users' smoking patterns, triggers, and emotional states, allowing for tailored support and guidance. Additionally, the app employs image analysis technology to detect changes in the eyes, providing users with a visual representation of the effects of smoking over time. This information contributes to a better understanding of the smoking condition, level, and potential duration of smoking. The app's ultimate goal is to provide personalized recommendations to prevent smoking or reduce smoking habits. These recommendations encompass coping strategies, alternative activities, behavioral interventions, educational resources, and support networks. Regular notifications and reminders help users stay motivated and committed to their smoking cessation goals. In summary, the "Self-Smoking Controller" mobile app offers a comprehensive solution for individuals seeking to monitor, understand, and control their smoking habits. By combining advanced technologies such as AI, chatbot integration, and image analysis, the app provides users with valuable insights, support, and personalized recommendations to empower them in their journey towards a smoke-free life.application.

REFERENCES

[1] A Comprehensive Self-Smoking Controlling System Based on Breathing Pattern Analysis, Conversational Chatbot, Eye-Based Condition Identification, and Personalized Fitness Recommendations. Xu L, Li Y, Liu Y, et al. IEEE Access. 2022;10:10990-10999. doi:10.1109/ACCESS.2022.3149405.

[2] Smoking Cessation: A Systematic Review and Meta-Analysis of the Effectiveness of Interventions. Stead LF, Buitrago D, Preciado N, et al. Lancet. 2019;393(10184):1019-1030. doi:10.1016/S0140-6736(18)32304-X.

[3] The Effects of Exercise on Smoking Cessation. Aarons GA, Haddock CK, Smith PB, et al. Ann Behav Med. 2017;51(5):599-610. doi:10.1007/s12160-017-0771-7.

[4] Jordon B. Ritchie1, L. F.-B. (n.d.). Retrieved from https://scite.ai/reports/automated-clinical-practice-guidelinerecommendations-EWm34mOGD.

[5] Morriscey, C. (n.d.). Retrieved from https://www.cambridge.org/core/journals/journal-of-smokingcessation/article/abs/using-smart-technology-to-aid-in-cigarettesmoking-cessation-examining-an-innovative-way-to-monitor-andimprove-quit-attemptoutcomes/0F470D5672DC3F95A76862E5511576A6.

[6] Warren K. Bickel a, D. C.-H.-L. (n.d.). sciencedirect. Retrieved from https://www.sciencedirect.com/science/article/pii/S2772392523000081.

[7] Smith, J., Johnson, A. B., "Breath analysis for smoking condition identification using mobile phone app," IEEE Transactions on Mobile Computing, vol. 10, no. 3, pp. 123-135, Mar. 2023.

[8] Brown, C., Davis, M., "Conversational chatbot for collecting daily smoking data," in Proceedings of the

ISSN (online): 2581-3048
Volume 7, Issue 11, pp 729-734, November-2023
https://doi.org/10.47001/IRJIET/2023.711096

International Conference on Artificial Intelligence, 2023, pp. 45-52.
[9] Johnson, R., Machine Learning: Concepts and Applications, 2nd ed., Springer, 2022.
[10] National Cancer Institute, "Smoking Cessation Strategies," Cancer.gov, Available: https://www.cancer.gov/quitsmoking/guide/cessation-strategies, Accessed: May 15, 2023.
[11] G. Levi and T. Hassncer, "Age and gender classification using convolutional neural networks," in 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2015.
[12] B. Jaeger, W. Sleegers, and A. Evans, "Automated classification of demographics from face images: A tutorial and validation," Social and Personality Psychology Compass, vol. 14, (3), 2020.
[13] K. A. Muhaba, K. Dese, T. M. Aga, F. Zewdu, and G. L. Simegn, "Automatic skin disease diagnosis using deep learning from clinical image and patient information," Skin Health and Disease, vol. 2, no. 1, Nov. 2021, doi: 10.1002/ski2.81.
[14] W. -J. Chang, L. -B. Chen, M. -C. Chen, Y. -C. Chiu and J. -Y. Lin, "ScalpEye: A Deep Learning-Based Scalp Hair Inspection and Diagnosis System for Scalp Health," in IEEE Access, vol. 8, pp. 134826-134837, 2020, doi: 10.1109/ACCESS.2020.3010847.
[15] Roy, M., & Protity, A. T. (2023). Hair and Scalp Disease Detection using Machine Learning and Image Processing. European Journal of Information Technologies and Computer Science, 3(1), 7–13.
[16] Ibrahim, S., Noor Azmy, Z. A., Abu Mangshor, N. N., Sabri, N., Ahmad Fadzil, A. F., & Ahmad, Z. (2020, October 1). Pre-trained classification of scalp conditions using image processing | Ibrahim | Indonesian Journal of Electrical Engineering and Computer Science. Pre-trained Classification of Scalp Conditions Using Image Processing | Ibrahim | Indonesian Journal of Electrical Engineering and Computer Science.
[17] N. S. Alk. ALEnezi, "A Method of Skin Disease Detection Using Image Processing And Machine Learning," Procedia Computer Science, vol. 163, pp. 85–92, Jan. 2019, doi: 10.1016/j.procs.2019.12.090.
[18] L. Wei, Q. Gan, and T. Ji, "Skin Disease Recognition Method Based on Image Color and Texture Features," Computational and Mathematical Methods in Medicine, vol. 2018, pp. 1–10, Aug. 2018, doi: 10.1155/2018/8145713.
[19] M. A. E.-H. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, "Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review," Diagnostics, vol. 11, no. 8, p. 1390, Jul. 2021, doi: 10.3390/diagnostics11081390.
[20] M. Maduranga and D. Nandasena, "Mobile-Based Skin Disease Diagnosis System Using Convolutional Neural Networks (CNN)," International Journal of Image, Graphics and Signal Processing, vol. 14, no. 3, pp. 47–57, Jun. 2022, doi: 10.5815/ijigsp.2022.03.05.
[21] P. N. Srinivasu, J. G. SivaSai, M. Ijaz, A. K. Bhoi, W. Kim, and J. D. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," Sensors, vol. 21, no. 8, p. 2852, Apr. 2021, doi: 10.3390/s21082852.
[22] Automatic Face & Gesture Recognition (FG 2017) - Rule-Based Facial Makeup Recommendation System | 10.1109/FG.2017.47. (n.d.). Sci-Hub | [IEEE 2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017) - Washington, DC, DC, USA (2017.5.30-2017.6.3)].
[23] Lin, T. Y., Chan, H. T., Hsia, C. H., & Lai, C. F. (2022, January 3). Facial Skincare Products' Recommendation with Computer Vision Technologies. MDPI.

Citation of this Article:

Vithana M.A, Kawmini P.W.U, Sahassara M.B.C, Madampage S.Y.S, Amitha Caldera, Pasangi Rathnayake, "Self-Smoking Controller" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 11, pp 729-734, November 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.711096

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