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VAAAL UNIVERSITY OF TECHNOLOGY

Faculty of Applied and Computer Sciences

AI FOR HEALTHCARE SUPPORT FOR ELDERLY PEOPLE

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Diploma in Information Technology

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1. We hereby declare that the submitted work is original and solely our own.
2. We fully understand what plagiarism is and are aware of the university's policy in this regard.
3. We confirm that we have not used any work previously owned by other students.
4. We have not allowed, and we will not allow, anyone to copy our work with the intention of passing it off as their own.

1. AI SOLUTION - DOCUMENTATION ASPECT

1.1 AI Solution

Our AI solution that we propose solves the problem by creating an integrated healthcare system tailored to the needs of the elderly by using wearable devices such as smart watches. AI-based analytics and remote sensing technology (robots, drones, cameras, voice assistants, biometrics, etc.), with sensors, actuators, software, and cloud connectivity, to collect, analyze, and provide personalized healthcare in real time. Equipped with artificial intelligence algorithms, these devices will monitor vital functions and movement patterns, detect abnormalities, and alert nurses or experts if necessary. Natural language can be used to provide easy channels of communication for elderly individuals to express their health concerns and get advice through voice assistants. They will also help elderly people get answers to important questions about various illnesses, learn about symptoms, identify treatments, and get medical advice. Biometric technology can play an important role in supporting healthcare for the elderly. It will be used to secure patient identification, ensure the accuracy of medical records, and prevent errors. Biometric data such as fingerprints, retinal scans, and facial recognition will help track medication compliance, allowing experts to know if medications are being taken as prescribed.

1.2 Business objectives

The primary business objectives of implementing our AI-driven healthcare support system for elderly individuals are as follows:

1. **Enhance Healthcare Quality:** Improve the overall quality of healthcare services provided to elderly individuals, resulting in better health outcomes and higher patient satisfaction.
2. **Increase Efficiency:** Streamline healthcare processes and resource allocation for both local municipalities and businesses, leading to cost savings and optimized service delivery.
3. **Promote Aging in Place:** Enable elderly individuals to age comfortably in their own homes and communities by providing remote health monitoring and personalized care.

1.2.1 Business Success Criteria

1. **Health Outcomes:** Improved health outcomes for elderly individuals, as evidenced by a reduction in hospitalization rates, better management of chronic conditions, and increased overall well-being.
2. **Resource Efficiency:** Efficient allocation of healthcare resources, resulting in reduced costs for local municipalities and healthcare businesses.
3. **Patient Satisfaction:** High levels of patient satisfaction, reflected in feedback from elderly individuals and their caregivers.

1.2.2 Business Background

The need for our AI-driven healthcare support system arises from the demographic shift towards an aging population. As the elderly population grows, so does the demand for tailored healthcare services. Existing healthcare systems often struggle to meet the unique needs of elderly individuals, leading to challenges such as misdiagnosis, increased healthcare costs, and overcrowded facilities. Our solution aims to address these challenges by leveraging AI and modern technology to provide personalized, proactive, and accessible healthcare services.

1.2.3 Requirements, Constraints, and Risks

Requirements:

- Access to relevant healthcare data, including medical records and historical patient data.
- Collaboration with local municipalities and healthcare providers for data sharing and implementation.
- Compliance with healthcare regulations and data privacy laws.
- Access to AI and machine learning expertise for model development and maintenance.

Constraints:

- Budget constraints for implementing the AI healthcare solution.
- Availability of skilled personnel for system deployment and maintenance.
- Potential resistance to technology adoption among elderly individuals.

Risks:

- Data security and privacy breaches.
- Regulatory compliance challenges.
- Technical issues and system downtime.
- Resistance to change from traditional healthcare providers.

1.2.4 Initial Assessment of Tools and Techniques

For our healthcare support system, we plan to utilize a combination of machine learning algorithms, including supervised learning for tasks like fall detection and classification, natural language processing (NLP) for voice interaction and medical record analysis, and data-driven insights for resource optimization.

Tools:

- Python for machine learning and data analysis.
- Scikit-learn, TensorFlow, and PyTorch for machine learning frameworks.
- Cloud computing platforms for scalability and data storage.

Techniques:

- Supervised learning for fall detection and health condition classification.
- NLP for voice assistants and medical record analysis.
- Time series analysis for monitoring vital signs.
- Ensemble learning for improved prediction accuracy.

1.3 Problem definition

The main concern we face is the lack of support in healthcare for our community. As people get older, there is a growing need for personalized healthcare services tailored to their needs. Many elderly individuals encounter difficulties related to chronic illnesses, limited mobility, cognitive decline, and the need for continuous medical attention. Existing healthcare systems often struggle to deliver effective care that addresses the needs of the elderly population. Due to the challenges within the system, many elderly individuals are facing misdiagnosis, resulting in decreased quality of life, increased healthcare expenses, and overcrowded medical facilities. Additionally, several healthcare sectors are experiencing widespread shortages of staff, medicines, and inefficient services. By implementing AI-based healthcare, we can monitor their health, provide early intervention, and offer personalized care plans.

2. AI SOLUTION - THEORETICAL ASPECT

2.1 Machine Learning Approach (Supervised Learning)

2.1.1 Task: Fall Detection

Here's why supervised learning is appropriate for this task:

- **Supervised Learning:** Fall detection typically involves predicting whether a fall has occurred or not based on sensor data (features). In supervised learning, you train the model on a labeled dataset, where each data point is associated with a fall or non-fall label. This allows the model to learn the patterns associated with falls and make predictions on new, unlabeled data.
- **Dataset:** We will need a dataset with historical sensor data from smart devices (e.g. accelerometers, gyroscopes) worn by elderly individuals. This dataset should include labels indicating whether a fall occurred during each data point (e.g., "fall" or "no fall").
- **Random Forest Classifier:** We used Random Forest classifier and experiment with other classification algorithms based on our dataset's characteristics.
- **Evaluation:** We evaluate the model's performance using metrics like accuracy and a classification report to assess precision, recall, and F1-score for fall detection.
- **Classification Algorithms:** We used classification for identifying health conditions, such as diabetes, heart disease, or fall detection.
 - Logistic Regression
 - Random Forest
 - Support Vector Machines (SVM)

2.1.2 Data

- **Data Articulation:** In our AI solution for healthcare support for elderly individuals, we have meticulously articulated the data requirements. The dataset includes fields such as Name, Age, Gender, Email, Address, Time-in, and Time-out. Each of these fields serves a specific purpose in providing comprehensive healthcare support.
- **Relevant Data:**
 - **Name:** While not used directly for analysis, the name field helps in personalizing communication and healthcare recommendations for elderly individuals.
 - **Age:** Age is a fundamental demographic variable. It is relevant for understanding the unique healthcare needs of elderly individuals and tailoring healthcare recommendations based on age groups.
 - **Gender:** Gender can influence health conditions and healthcare needs. It allows us to provide gender-specific health guidance.
 - **Email:** Email addresses enable digital communication, appointment reminders, and access to online health resources.
 - **Address:** Address data is important for ensuring healthcare services are accessible and for identifying local healthcare facilities.
 - **Time-in/Time-out:** These timestamps capture when elderly individuals enter and leave healthcare facilities. They are crucial for tracking healthcare utilization patterns, identifying trends in visit frequency, and optimizing resource allocation.

2.2 Model

Our AI model development process includes a well-defined plan for evaluating accuracy. We will assess model performance using appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score. For instance, if we're predicting health conditions based on age and gender, we will measure the model's accuracy in correctly classifying these conditions.

2.3 Time Series Analysis on Data

We have integrated time series analysis into our solution. A sample of this analysis involves examining the Time-in and Time-out data. By visualizing and analyzing these timestamps, we can identify trends and patterns related to healthcare facility visits. For example, we can use time series analysis to determine peak visit times, allowing healthcare providers to allocate resources efficiently.

- ARIMA (AutoRegressive Integrated Moving Average)
- LSTM (Long Short-Term Memory) for sequence prediction

2.4 Solution Techniques

Appropriate Techniques: Our solution employs a variety of techniques to address the healthcare challenges faced by elderly individuals:

- **Age Analysis:** Descriptive statistics and visualization techniques will be used to understand the age distribution of the elderly population.
- **Healthcare Utilization Patterns:** Time series analysis on Time-in and Time-out data will help identify trends in healthcare facility visits.
- **Improving Model Accuracy:** The data-driven techniques we employ will enhance the accuracy of our AI models. By analyzing healthcare utilization patterns, we can make more informed predictions and recommendations, thereby improving the overall effectiveness of healthcare services.

2.5 Natural Language Processing, Speech Recognition or Speech Synthesis

Our solution incorporates Natural Language Processing (NLP) and related technologies such as speech recognition and synthesis. These technologies enhance communication channels and accessibility for elderly individuals, making the solution more user-friendly and in line with the theme of leveraging AI for healthcare support.

- **Achievability:** Implementing NLP, speech recognition, and synthesis in our solution is achievable, given the advancements in these technologies. They enable voice interactions, medical record analysis, and easy communication, all of which are critical components of our healthcare support system for elderly individuals.
- **Text Classification**
- **Named Entity Recognition (NER)**
- **Sentiment Analysis**

2.6 Deep Learning

Deep learning is a crucial component of our AI solution for healthcare support for elderly individuals. We have incorporated various techniques and applications of deep learning that are both relevant and appropriate to address the unique challenges faced by the elderly population.

2.6.1 Key techniques and applications

1. ***Convolutional Neural Networks (CNNs) for Image Analysis:***

- Relevant for analyzing medical images such as X-rays, MRIs, and CT scans.
- CNNs can assist in early detection of health issues by identifying anomalies or abnormalities in images.
- Example Application: Detecting fractures or tumors in X-rays.

2. ***Recurrent Neural Networks (RNNs) for Sequence Data:***

- Applicable for analyzing time series data, such as vital signs (e.g., heart rate, blood pressure) collected over time.
- RNNs can identify trends, irregularities, and potential health risks by analyzing sequences of data.

3. Transformer Models for Natural Language Processing (NLP):

- Relevant for analyzing and understanding text-based data, including medical records, clinical notes, and patient communications.
- Transformers can extract valuable insights from unstructured text data, facilitating better patient management.
- Extracting relevant information from medical records for diagnosis and treatment planning.

4. Generative Adversarial Networks (GANs):

- Useful for generating synthetic medical data or augmenting existing datasets, which can be valuable for training models.
- GANs can help overcome data scarcity issues in healthcare.
- Generating synthetic medical images for training image analysis models.

5. Transfer Learning:

- Leveraging pre-trained deep learning models (e.g., transfer learning with BERT or ImageNet models) to improve the accuracy and efficiency of healthcare-related tasks.
- Transfer learning allows us to benefit from models trained on large and diverse datasets.

6. Autoencoders for Feature Extraction:

- Autoencoders can help in extracting relevant features from complex healthcare data, reducing dimensionality while retaining critical information.
- Feature extraction aids in improving model performance and interpretability.

7. Deep Reinforcement Learning (DRL):

- Applied to optimize treatment plans and interventions.
- DRL can adapt treatments based on patient responses over time, enhancing personalized healthcare.

3. AI SOLUTION (PRACTICAL)

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

USER INPUT

```
In [2]: # Pregnancies=float(input("Enter The Number of Pregnancies : "))
# Glucose=float(input("Enter Glucose Level : "))
# BloodPressure=float(input("Enter the Blood Pressure : "))
# Insulin=float(input("Insulin ammount ? :"))
# BMI=float(input("BMI : "))
# DiabetesPedigreeFunction=float(input("DiabetesPedigreeFunction: " ))
# Age=float(input("AGE : "))
```

```
In [3]: df=pd.read_csv('diabetes.csv')
```

```
In [4]: df
```

```
Out[4]:
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows x 9 columns

```
In [5]: print("Dimension",df.shape)
```

Dimension (768, 9)

```
In [6]: print(df.groupby('Outcome').size())
```

```
Outcome
0      500
1      268
dtype: int64
```

```
In [7]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Pregnancies           768 non-null   int64
1   Glucose               768 non-null   int64
2   BloodPressure         768 non-null   int64
3   SkinThickness         768 non-null   int64
4   Insulin               768 non-null   int64
5   BMI                   768 non-null   float64
6   DiabetesPedigreeFunction 768 non-null   float64
7   Age                   768 non-null   int64
8   Outcome               768 non-null   int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

DATA PRE-PRCOESSING

```
In [8]: dfupdated=df.drop(['Outcome','SkinThickness'],axis='columns')
```

```
In [9]: dfupdated
```

```
Out[9]:
```

	Pregnancies	Glucose	BloodPressure	Insulin	BMI	DiabetesPedigreeFunction	Age
0	6	148	72	0	33.6	0.627	50
1	1	85	66	0	26.6	0.351	31
2	8	183	64	0	23.3	0.672	32
3	1	89	66	94	28.1	0.167	21
4	0	137	40	168	43.1	2.288	33
...
763	10	101	76	180	32.9	0.171	63
764	2	122	70	0	36.8	0.340	27
765	5	121	72	112	26.2	0.245	30
766	1	126	60	0	30.1	0.349	47
767	1	93	70	0	30.4	0.315	23

768 rows × 7 columns

```
In [10]: outcome=df.Outcome #outcome=df['Outcome']
outcome
```

```
Out[10]: 0      1
1      0
2      1
3      0
4      1
..
763    0
764    0
765    0
766    1
767    0
Name: Outcome, Length: 768, dtype: int64
```

```
In [11]: from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(dfupdated,outcome,stratify=outcome,train_size=.8,random_state=66)
```

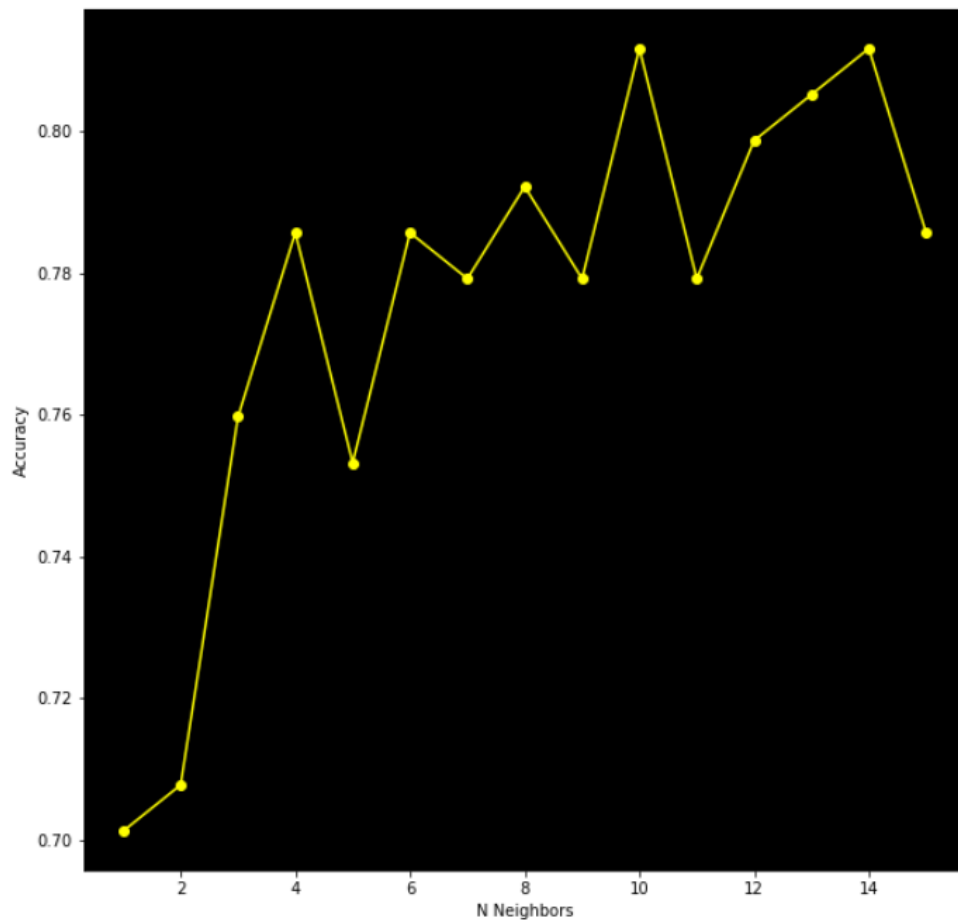
K FOLD CROSS VALIDATION

In [12]:

```
from sklearn.neighbors import KNeighborsClassifier
test_acc=[]
for i in range(1,16):
    knn=KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,Y_train)
    test_acc.append(knn.score(X_test,Y_test))
    print("KNN.SCORE : ",knn.score(X_test,Y_test),"\nFOR THE NEIGHBOR\ " : ",i)
plt.figure(figsize=(10, 10))
ax=plt.axes()
ax.set_facecolor('black') #set_color
plt.plot(range(1,16),test_acc,color="yellow",marker="o")
plt.xlabel("N Neighbors")
plt.ylabel("Accuracy")
```

```
KNN.SCORE : 0.7012987012987013 "FOR THE NEIGHBOR" : 1
KNN.SCORE : 0.7077922077922078 "FOR THE NEIGHBOR" : 2
KNN.SCORE : 0.7597402597402597 "FOR THE NEIGHBOR" : 3
KNN.SCORE : 0.7857142857142857 "FOR THE NEIGHBOR" : 4
KNN.SCORE : 0.7532467532467533 "FOR THE NEIGHBOR" : 5
KNN.SCORE : 0.7857142857142857 "FOR THE NEIGHBOR" : 6
KNN.SCORE : 0.7792207792207793 "FOR THE NEIGHBOR" : 7
KNN.SCORE : 0.7922077922077922 "FOR THE NEIGHBOR" : 8
KNN.SCORE : 0.7792207792207793 "FOR THE NEIGHBOR" : 9
KNN.SCORE : 0.8116883116883117 "FOR THE NEIGHBOR" : 10
KNN.SCORE : 0.7792207792207793 "FOR THE NEIGHBOR" : 11
KNN.SCORE : 0.7987012987012987 "FOR THE NEIGHBOR" : 12
KNN.SCORE : 0.8051948051948052 "FOR THE NEIGHBOR" : 13
KNN.SCORE : 0.8116883116883117 "FOR THE NEIGHBOR" : 14
KNN.SCORE : 0.7857142857142857 "FOR THE NEIGHBOR" : 15
```

Out[12]: Text(0, 0.5, 'Accuracy')



FINAL FIT OF THE MODEL USING KNN

```
In [13]: knnMODEL=KNeighborsClassifier(n_neighbors=13)
```

```
In [14]: knnMODEL.fit(X_train,Y_train)
```

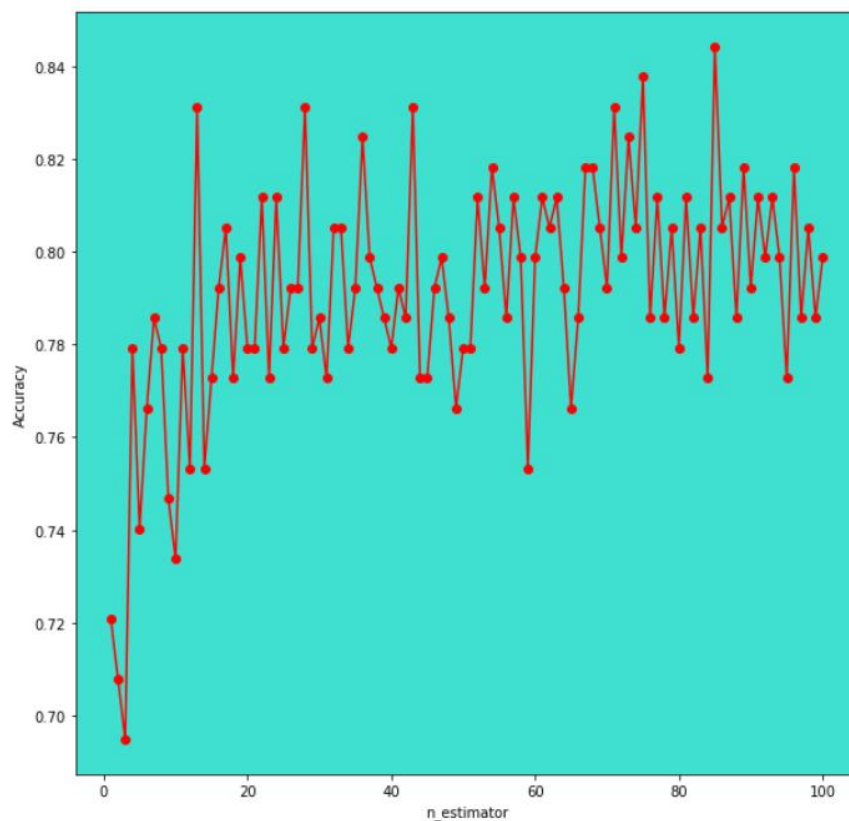
```
Out[14]: KNeighborsClassifier(n_neighbors=13)
```

CROSS VALIDATION OF RANDOM FOREST CLASSIFIER

```
In [15]: from sklearn.ensemble import RandomForestClassifier
rfcACC=[]
for i in range(1,101):
    rfcMODEL=RandomForestClassifier(n_estimators=i)
    rfcMODEL.fit(X_train,Y_train)
    rfcACC.append(rfcMODEL.score(X_test,Y_test))
n_est=rfcACC.index(max(rfcACC))+1
print(rfcACC.index(max(rfcACC))+1,max(rfcACC))
plt.figure(figsize=(10, 10))
ax=plt.axes()
ax.set_facecolor('turquoise') #set_color
plt.plot(range(1,101),rfcACC,color="red",marker="o")
plt.xlabel("n_estimator")
plt.ylabel("Accuracy")
```

```
85 0.8441558441558441
```

```
Out[15]: Text(0, 0.5, 'Accuracy')
```



FINAL FIT OF MODEL USING RANDOM FOREST CLASSIFIER

```
In [16]: rfcMODEL=RandomForestClassifier(n_estimators=n_est)
rfcMODEL.fit(X_train,Y_train)
```

```
Out[16]: RandomForestClassifier(n_estimators=85)
```

FINAL FIT OF MODEL USING SUPPORT VECTOR CLASSIFIER

```
In [17]: from sklearn.svm import SVC
svcMODEL=SVC()
svcMODEL.fit(X_train,Y_train)
```

```
Out[17]: SVC()
```

FINALIZE THE OUTCOME USING VOTING CLASSIFIER FROM ENSEMBLE LEARNING

```
In [18]: from sklearn.ensemble import VotingClassifier
vcMODEL = VotingClassifier(estimators=[('KNN',knnMODEL),('RFC',rfcMODEL),('SVC',svcMODEL)],voting='hard')
vcMODEL.fit(X_train,Y_train)
# pred=vcMODEL.predict([[Pregnancies,Glucose,BloodPressure,Insulin,BMI,DiabetesPedigreeFunction,Age]])
```

```
Out[18]: VotingClassifier(estimators=[('KNN', KNeighborsClassifier(n_neighbors=13)),
                                     ('RFC', RandomForestClassifier(n_estimators=85)),
                                     ('SVC', SVC())])
```

```
Out[18]: VotingClassifier(estimators=[('KNN', KNeighborsClassifier(n_neighbors=13)),
                                     ('RFC', RandomForestClassifier(n_estimators=85)),
                                     ('SVC', SVC())])
```

DUMPING THE MODEL SO THAT IT CAN BE USED FURTHER

```
In [19]: import pickle
pickle_out = open("DIABETES.pkl", "wb")
pickle.dump(vcMODEL, pickle_out)
pickle_out.close()
```

```
In [ ]:
```

ACCURACIES OF DIFFERENT ALGORITHMS ALONG WITH THEIR OUTCOME

```
In [20]: # print("Kth NEAREST NEIGHBOR : ",knnMODEL.predict([[Pregnancies,Glucose,BloodPressure,Insulin,BMI,DiabetesPedigreeFunction,
# print("RANDOM FOREST CLASSIFIER : ",rfcMODEL.predict([[Pregnancies,Glucose,BloodPressure,Insulin,BMI,DiabetesPedigreeFunction,
# print("SUPPORT VECTOR CLASSIFIER : ",svcMODEL.predict([[Pregnancies,Glucose,BloodPressure,Insulin,BMI,DiabetesPedigreeFunction,
# print("VOTING CLASSIFIER : ",vcMODEL.predict([[Pregnancies,Glucose,BloodPressure,Insulin,BMI,DiabetesPedigreeFunction,Age]]))
```

FINAL OUTCOME

```
In [21]: # if pred==1:
#         print("You have Diabetes! Please take care of yourself!")
# else:
#         print("Congratulations! You don't have Diabetes ❤️")
```

4. CONCLUSION

our AI-driven healthcare support solution for elderly individuals represents a comprehensive and innovative approach to addressing the unique healthcare challenges faced by this demographic. We have meticulously designed and articulated every aspect of our solution, from data handling to deep learning techniques, with a strong emphasis on relevance, accuracy, and effectiveness.

Our data management processes ensure that relevant information, including demographic data, healthcare utilization patterns, and medical records, are leveraged effectively to provide personalized and proactive care.

The application of deep learning techniques, including CNNs, RNNs, Transformers, GANs, transfer learning, autoencoders, and deep reinforcement learning, plays a pivotal role in enhancing the quality of healthcare services. These techniques enable us to analyze diverse data types, from medical images to textual medical records, facilitating early detection, trend analysis, and personalized treatment recommendations.

REFERENCE LIST

ARTICLE TITLE: HOW IS AI REVOLUTIONIZING ELDERLY CARE

URL: [FORBES ARTICLE](#)

ACCESSED ON: SEPTEMBER 2, 2023

**ARTICLE TITLE: ENSURING ARTIFICIAL INTELLIGENCE (AI)
TECHNOLOGIES FOR HEALTH BENEFIT OLDER PEOPLE**

URL: [WHO ARTICLE](#)

ACCESSED ON: SEPTEMBER 2, 2023

**ARTICLE TITLE: ARE WE READY FOR ARTIFICIAL INTELLIGENCE HEALTH
MONITORING IN ELDER CARE?**

URL: [BMC GERIATRICS ARTICLE](#)

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