1. Clean, Integrate and Transform Electronic Healthcare Records.
2. Apply various data analysis and visualization techniques on EHR,
3. Bio Medical Image Preprocessing, Segmentation
4. Bio Medical Image Analytics.
5. Text Analytics for Clinical Text Data
6. Diagnose disease risk from Patient data
7. Social Media Analytics for outbreak prediction/ Drug review analytics.
8. Visual Analytics for Healthcare Data

Experiment 1: Clean, Integrate and Transform Electronic Healthcare Records (EHR)

Aim:
To clean, integrate, and transform Electronic Healthcare Records for meaningful data analysis.

Theory:

- Electronic Healthcare Records (EHRs) are digital records that store patient information such as demographics, diagnoses, medications, and lab results.

- Raw EHR data is often incomplete, inconsistent, duplicated, or contains errors due to multiple sources of entry.

- **Data Cleaning** involves:

  - Handling missing values (e.g., imputation or removal).

  - Removing duplicates and correcting errors.

  - Standardizing formats (dates, codes, measurements).

- **Data Integration** combines EHR data from various sources (hospitals, labs, pharmacies) into a unified dataset.

- **Data Transformation** includes normalization, encoding categorical values, and feature extraction for analysis.

- These steps ensure high-quality data, which is crucial for accurate healthcare analytics and research.

Conclusion:
EHR cleaning, integration, and transformation improve data quality, making it reliable for advanced healthcare analytics and better patient outcomes.

Experiment 2: Apply Various Data Analysis and Visualization Techniques on EHR

Aim:
To perform data analysis and apply visualization techniques on Electronic Healthcare Records.

Theory:

- Healthcare datasets contain patient demographics, medical history, prescriptions, and diagnostic results.

- **Data Analysis Types:**

  - Descriptive analysis → Summarizes patient data (e.g., average age, disease counts).

  - Diagnostic analysis → Identifies causes of diseases or abnormal patterns.

  - Predictive analysis → Forecasts disease risks or outcomes using models.

  - Prescriptive analysis → Suggests best treatments or preventive actions.

- **Visualization Techniques:**

  - Histograms and bar charts → Distribution of patients by age, gender, or disease.

  - Scatter plots → Relationship between risk factors (e.g., blood pressure vs. heart disease).

  - Heatmaps → Correlation between different medical attributes.

  - Dashboards → Interactive representation for doctors and administrators.

- Tools: Python (Matplotlib, Seaborn), Power BI, Tableau, or R.

Conclusion:
Data analysis and visualization provide actionable insights from EHR, helping healthcare professionals make evidence-based decisions.

Experiment 3: Biomedical Image Preprocessing and Segmentation

Aim:
To preprocess and segment biomedical images for further medical analysis.

Theory:

- Biomedical images include MRI, CT, X-rays, PET scans, and ultrasound.

- Raw images often suffer from **noise, low contrast, or artifacts**.

- **Preprocessing techniques:**

    - Noise reduction using filters (Gaussian, median).

    - Normalization and contrast adjustment.

    - Image resizing and standardization.

- **Segmentation techniques:**

    - Thresholding → Separating regions based on pixel intensity.

    - Edge detection → Identifying boundaries of organs or tissues.

    - Clustering methods (K-means, region growing).

    - Deep learning models (U-Net, Mask R-CNN) for advanced segmentation.

- Segmentation highlights regions of interest such as tumors, organs, or lesions, which supports diagnosis.

Conclusion:
Preprocessing and segmentation improve biomedical image quality and help doctors focus on critical regions for diagnosis.

Experiment 4: Biomedical Image Analysis

Aim:
To analyze biomedical images using computational and statistical techniques.

Theory:

- Biomedical image analysis extracts quantitative and qualitative information from medical images.

- **Steps in analysis:**

  - Image acquisition → Capturing raw data from imaging devices.

  - Preprocessing → Enhancing image quality.

  - Feature extraction → Identifying texture, shape, intensity patterns.

  - Classification → Distinguishing between normal and abnormal tissues.

- **Applications:**

  - Tumor detection (brain, lung, breast cancers).

  - Identifying fractures or abnormalities in bones.

  - Monitoring disease progression (e.g., Alzheimer's via MRI scans).

- **Techniques used:**

  - Statistical pattern recognition.

  - Machine learning models (SVM, CNNs).

  - Image similarity and clustering methods.

Conclusion:
Biomedical image analysis provides critical insights for early disease detection, accurate diagnosis, and personalized healthcare.

Experiment 5: Text Analytics for Clinical Text Data

Aim:
To apply text analytics techniques to clinical text data for extracting meaningful information.

Theory:

- Clinical data includes unstructured records like discharge summaries, prescriptions, and doctor notes.

- **Challenges:** Text may contain medical abbreviations, spelling variations, and ambiguous terms.

- **Text preprocessing steps:**

  - Tokenization → Breaking sentences into words.

  - Stopword removal → Removing common words (e.g., "the," "is").

  - Lemmatization/Stemming → Reducing words to base form.

- **Text Analytics methods:**

  - Named Entity Recognition (NER) → Identifying diseases, drugs, symptoms.

  - Topic modeling → Discovering hidden themes (e.g., patient complaints).

  - Sentiment analysis → Evaluating patient reviews and feedback.

- Applications: Clinical decision support, electronic health record mining, medical research.

Conclusion:
Text analytics converts unstructured medical documents into structured data, enabling effective decision-making and healthcare research.

Experiment 6: Diagnose Disease Risk from Patient Data

Aim:
To diagnose disease risk from patient data using data analysis and predictive modeling techniques.

Theory:

- Patient data includes demographics, vitals, lifestyle information, and lab results.

- Disease risk models are built using statistical and machine learning methods.

- **Techniques:**

  - Logistic regression → Probability of disease occurrence.

  - Decision trees & Random Forests → Risk classification.

  - Neural networks → Complex pattern recognition in patient data.

  - Risk scoring models → Assigning patients into low, medium, high-risk groups.

- **Applications:**

  - Predicting diabetes based on BMI, glucose, and family history.

  - Heart disease risk from cholesterol, ECG readings, and blood pressure.

  - Cancer risk prediction using genetic and lifestyle data.

Conclusion:
Disease risk prediction enables proactive healthcare, early interventions, and tailored treatment for patients.

Experiment 7: Social Media Analytics for Outbreak Prediction / Drug Review Analytics

Aim:
To analyze social media data for outbreak prediction and drug review analytics.

Theory:

- Social media platforms capture real-time patient experiences and outbreak signals.

- **Outbreak prediction:**

  - Monitoring hashtags and keywords (e.g., "fever," "flu") for unusual spikes.

  - Trend analysis to detect epidemic spread.

- **Drug review analytics:**

- ○ Collecting patient opinions from forums, blogs, or reviews.

- ○ Sentiment analysis to classify reviews as positive, negative, or neutral.

- ○ Identifying side effects and drug effectiveness.

- **Techniques used:**

  - ○ NLP for text processing.

  - ○ Topic modeling for clustering discussions.

  - ○ Machine learning for classification and trend prediction.

- Applications: Early-warning systems for pandemics, pharmacovigilance, and patient awareness.

Conclusion:
Social media analytics offers real-time insights into disease outbreaks and drug safety, helping public health authorities and pharmaceutical companies.

Experiment 8: Visual Analytics for Healthcare Data

Aim:
To apply visual analytics techniques to healthcare datasets for better understanding and decision-making.

Theory:

- Visual analytics combines data visualization with analytical reasoning.

- **Features of visual analytics:**

  - ○ Dashboards → Summarizing key health metrics.

  - ○ Interactive charts → Allow filtering and drill-down for detailed views.

  - ○ Geographic maps → Showing disease spread across regions.

- **Techniques:**

- ○ Time series plots → Tracking patient vitals or outbreak trends.

- ○ Correlation matrices → Identifying relationships between medical attributes.

- ○ Heatmaps and tree maps → Highlighting clusters of data.

- Tools: Tableau, Power BI, Python libraries (Matplotlib, Seaborn, Plotly).

- Applications: Hospital management, disease monitoring, resource allocation, patient outcome tracking.

Conclusion:
Visual analytics transforms raw healthcare data into interactive and insightful dashboards, improving clinical and administrative decision-making.