ANON STUDIOS 254 PRESENTS AUTOMATA SCHOOL OF KENYA

OUR 6 MONTHS ROADMAP

Month 0😅

30-Day AI, ML, and DL Course

Day 1: Introduction to AI, ML, and DL
- What is Artificial Intelligence (AI)?
- Overview of Machine Learning (ML) and Deep Learning (DL)
- Applications of AI, ML, and DL in various industries

Day 2: Fundamentals of Machine Learning
- Supervised, Unsupervised, and Reinforcement Learning
- Types of ML algorithms (Linear Regression, Logistic Regression, Decision Trees, etc.)
- Importance of data preprocessing and feature engineering

Day 3: Introduction to Python and NumPy
- Python programming basics
- Numpy library for numerical computing
- Working with arrays and matrices

Day 4: Exploratory Data Analysis (EDA)
- Importing and visualizing data
- Identifying patterns, trends, and outliers
- Handling missing data and data cleaning

Day 5: Linear Regression
- Understanding the concept of linear regression
- Implementing linear regression using Python
- Evaluating model performance (R-squared, MSE, RMSE)

Day 6: Logistic Regression
- Introduction to classification problems
- Logistic regression algorithm and its applications
- Implementing logistic regression in Python

Day 7: Decision Trees
- Concept of decision trees
- Building and visualizing decision trees
- Advantages and limitations of decision trees

Day 8: Random Forests
- Ensemble learning and the random forest algorithm
- Hyperparameter tuning and feature importance
- Implementing random forests in Python

Day 9: Support Vector Machines (SVMs)
- Understanding the SVM algorithm
- Kernel functions and the kernel trick
- Implementing SVMs in Python

Day 10: K-Nearest Neighbors (KNN)
- Concept of KNN algorithm
- Distance metrics and hyperparameter tuning
- Implementing KNN in Python

Day 11: Clustering Algorithms
- K-Means clustering
- Hierarchical clustering
- DBSCAN clustering

Day 12: Dimensionality Reduction
- Principal Component Analysis (PCA)
- t-SNE (t-Distributed Stochastic Neighbor Embedding)
- Implementing dimensionality reduction in Python

Day 13: Introduction to Deep Learning
- Artificial Neural Networks (ANNs)
- Activation functions and network architectures
- Backpropagation algorithm

Day 14: Convolutional Neural Networks (CNNs)
- Convolutional layers and pooling layers
- Applications of CNNs in image recognition
- Implementing CNNs in Python

Day 15: Recurrent Neural Networks (RNNs)
- Sequence data and time series problems
- Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)
- Applying RNNs to text and time series data

Day 16: Generative Adversarial Networks (GANs)
- Generative models and their applications
- GAN architecture and training process
- Implementing GANs in Python

Day 17: Reinforcement Learning
- Markov Decision Processes (MDPs)
- Q-learning and policy gradients
- Applications of reinforcement learning

Day 18: Unsupervised Learning Techniques
- Autoencoders
- Variational Autoencoders (VAEs)
- Generative Adversarial Networks (GANs)

Day 19: Model Evaluation and Optimization
- Bias-Variance Tradeoff
- Overfitting and Underfitting
- Hyperparameter Tuning and Cross-Validation

Day 20: Introduction to Natural Language Processing (NLP)
- Text preprocessing and cleaning
- Tokenization and word embeddings
- Sentiment analysis and text classification

Day 21: Text Preprocessing and Feature Engineering
- Handling missing data and outliers in text data
- Feature extraction techniques (bag-of-words, TF-IDF, etc.)
- Dimensionality reduction for text data

Day 22: Classical NLP Algorithms
- Naive Bayes Classifier
- Logistic Regression for text classification
- Support Vector Machines for text classification

Day 23: Deep Learning for NLP
- Recurrent Neural Networks (RNNs) for text data
- Long Short-Term Memory (LSTMs) and Gated Recurrent Units (GRUs)
- Transformer models (BERT, GPT, etc.)

Day 24: Named Entity Recognition (NER)
- Sequence labeling and BIO tagging
- Implementing NER using Conditional Random Fields (CRFs)
- Applying deep learning models for NER

Day 25: Text Generation
- Language modeling and next-word prediction
- Generating text using Recurrent Neural Networks
- Implementing text generation with Transformer models

Day 26: Question Answering
- Extractive and Abstractive Question Answering
- Implementing QA systems using Transformer models
- Evaluating QA models using metrics like F1 and Exact Match

Day 27: Dialogue Systems and Chatbots
- Retrieval-based and Generation-based chatbots
- Implementing a simple chatbot using Sequence-to-Sequence models
- Conversational AI and virtual assistants

Day 28: Multilingual NLP
- Cross-lingual word embeddings
- Machine translation using Transformer models
- Multilingual text classification and NER

Day 29: NLP Applications in the Real World
- Customer service and support automation
- Sentiment analysis for social media monitoring
- Summarization and document understanding

Day 30: Ethical Considerations in NLP
- Bias and fairness in NLP models
- Privacy and data protection in NLP applications
- Responsible development and deployment of NLP systems

Month 1

WEEK 1 AND 2
Week 1: Introduction to AI, DL, and ML

Day 1: What is Artificial Intelligence?
- Definition and brief history of AI
- Subfields of AI: Machine Learning, Deep Learning, Natural Language Processing, and more
- Applications of AI across industries

Day 2: Fundamentals of Machine Learning
- Key concepts of Machine Learning (ML)
- Supervised, Unsupervised, and Reinforcement Learning
- Types of ML algorithms: Regression, Classification, Clustering, and more
- Importance of data in Machine Learning

Day 3: Introduction to Deep Learning

- Understanding Deep Learning (DL) and its relationship to Machine Learning
- Artificial Neural Networks: structure, activation functions, and layers
- Convolutional Neural Networks (CNNs) and their applications
- Recurrent Neural Networks (RNNs) and their use in sequence-based tasks

Day 4: Mathematics for AI: Linear Algebra Basics
- Vectors, matrices, and their operations
- Matrix multiplication and its properties
- Eigenvalues and eigenvectors
- Applications of linear algebra in ML and DL

Day 5: Mathematics for AI: Calculus for Optimization
- Differentiation and partial derivatives
- Gradients and their role in optimization
- Optimization techniques: Gradient Descent, Stochastic Gradient Descent
- Intuition behind backpropagation algorithm

Day 6: Mathematics for AI: Mathematical Analysis for Algorithms
- Understanding the complexity of algorithms
- Big O notation and its importance in algorithm analysis
- Differential calculus and its applications in algorithm design
- Optimization techniques and their mathematical foundations

Day 7: Project: Implementing a Simple Machine Learning Model
- Hands-on project to apply the concepts learned so far
- Choosing an appropriate ML algorithm for a given problem
- Preprocessing data and training the model
- Evaluating model performance

Week 2: Deeper Dive into AI, DL, and ML

Day 8: Advanced Topics in Machine Learning
- Ensemble methods: Bagging, Boosting, and Random Forests
- Support Vector Machines (SVMs) and their applications
- Decision Trees and their interpretability
- Dimensionality reduction techniques

Day 9: Deep Learning Architectures
- Feedforward Neural Networks
- Convolutional Neural Networks (CNNs) and their applications
- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs)

- Generative Adversarial Networks (GANs)
Day 10: Optimization Techniques in Deep Learning
- Gradient-based optimization methods
- Momentum, Nesterov Accelerated Gradient, and Adaptive Techniques
- Batch Normalization and its impact on training
- Regularization techniques to prevent overfitting

Day 11: Mathematics for AI: Probability and Statistics
- Probability distributions and their properties
- Bayes' Theorem and its applications in ML
- Statistical inference and hypothesis testing
- Correlation and regression analysis

Day 12: Mathematics for AI: Information Theory and Entropy
- Information theory and its relevance in ML and DL
- Entropy, mutual information, and Kullback-Leibler divergence
- Applications of information theory in model evaluation and optimization

Day 13: Mathematics for AI: Numerical Optimization
- Convex optimization and its properties
- Gradient-based optimization methods
- Constrained optimization and Lagrange multipliers
- Numerical methods for solving optimization problems

Day 14: Project: Implementing a Deep Learning Model
- Hands-on project to apply the concepts learned so far
- Choosing an appropriate DL architecture for a given problem
- Preprocessing data and training the model
- Evaluating model performance and fine-tuning

WEEK 3 AND 4

Week 3: Statistics for Machine Learning

Day 1: Measures of Central Tendency and Variability
- Mean, median, and mode
- Measures of variability: range, variance, and standard deviation
- Understanding the importance of these measures in data analysis

Day 2: Correlation and Covariance
- Definition and calculation of correlation and covariance
- Understanding the difference between correlation and causation

- Applications of correlation in data analysis

Day 3: Central Limit Theorem (CLT)
- Understanding the CLT and its implications for sampling distributions
- How the CLT affects hypothesis testing and confidence intervals
- Practical applications of the CLT in data analysis

Day 4: Hypothesis Testing
- Introduction to hypothesis testing and its importance in ML
- Types of hypothesis tests: one-tailed and two-tailed tests
- Understanding p-values and significance testing

Day 5: Probability and Sampling Techniques
- Probability distributions and their properties
- Random sampling and its importance in data analysis
- Understanding the difference between random sampling and stratified sampling

Day 6: AB Testing and Experimentation
- Introduction to AB testing and its role in AI experimentation
- Designing and conducting AB tests effectively
- Understanding the importance of statistical significance in AB testing

Day 7: Increasing Test Sensitivity and Handling Ratio Metrics
- Strategies for increasing test sensitivity
- Understanding ratio metrics and how to handle them effectively
- Practical applications of these techniques in data analysis

Week 4: Advanced Statistics for Machine Learning

Day 8: Nonparametric Statistics
- Introduction to nonparametric statistics and its applications in ML
- Understanding the difference between parametric and nonparametric tests
- Practical applications of nonparametric tests in data analysis

Day 9: Bayesian Statistics
- Introduction to Bayesian statistics and its applications in ML
- Understanding the Bayesian approach to hypothesis testing
- Practical applications of Bayesian statistics in data analysis

Day 10: Time Series Analysis
- Introduction to time series analysis and its importance in ML
- Understanding the difference between time series and cross-sectional data
- Practical applications of time series analysis in data analysis

Day 11: Clustering and Dimensionality Reduction
- Introduction to clustering and dimensionality reduction techniques
- Understanding the importance of dimensionality reduction in ML
- Practical applications of clustering and dimensionality reduction techniques in data analysis

Day 12: Regression Analysis
- Introduction to regression analysis and its importance in ML
- Understanding the difference between linear and non-linear regression
- Practical applications of regression analysis in data analysis

Day 13: Multivariate Analysis
- Introduction to multivariate analysis and its importance in ML
- Understanding the difference between univariate and multivariate analysis
- Practical applications of multivariate analysis in data analysis

Day 14: Project: Applying Statistics to Machine Learning
- Hands-on project to apply the concepts learned so far
- Choosing a suitable statistical method for a given ML problem
- Preprocessing data and applying the chosen statistical method
- Evaluating the results and interpreting the findings

Month 2

WEEK 5 AND 6

Week 5: Econometrics for AI

Day 1: Introduction to Econometrics

- What is Econometrics and why is it important for AI?

- Fundamental economic concepts: supply, demand, equilibrium, and market dynamics

- The role of econometrics in understanding and modeling economic phenomena

Day 2: Regression Analysis for Predictive Modeling

- Simple and multiple linear regression

- Assumptions of linear regression and their importance

- Interpreting regression coefficients and model fit

Day 3: Regression Diagnostics and Validation

- Assessing model assumptions: linearity, homoscedasticity, and normality

- Dealing with multicollinearity and heteroscedasticity

- Techniques for model validation, such as cross-validation and holdout testing

Day 4: Time Series Analysis

- Introduction to time series data and its characteristics

- Stationarity and non-stationarity in time series

- Autoregressive (AR), Moving Average (MA), and ARIMA models

Day 5: Forecasting with Time Series Models

- Forecasting techniques: exponential smoothing, ARIMA, and vector autoregression

- Evaluating forecast accuracy and model performance

- Incorporating exogenous variables in time series models

Day 6: Probability Distributions and Probabilistic Modeling

- Fitting probability distributions to data

- Understanding the role of probability distributions in AI applications

- Estimating parameters of probability distributions

Day 7: Project: Applying Econometrics to an AI Problem

- Hands-on project to apply the concepts learned so far

- Choosing an appropriate econometric technique for a given AI problem

- Preprocessing data and fitting the econometric model

- Evaluating model performance and interpreting the results

Week 6: Advanced Econometrics for AI

Day 8: Discrete Choice Models

- Introduction to discrete choice models and their applications in AI

- Logit and probit models for binary and multinomial choices

- Interpreting and evaluating discrete choice models

Day 9: Panel Data Analysis

- Understanding panel data and its advantages over cross-sectional or time series data

- Fixed effects and random effects models

- Applying panel data analysis to AI problems

Day 10: Instrumental Variables and Two-Stage Least Squares

- Addressing endogeneity issues in regression models

- Instrumental variables and their properties

- Two-stage least squares (2SLS) estimation

Day 11: Difference-in-Differences and Causal Inference

- Causal inference and the potential outcomes framework

- Difference-in-differences (DID) method for estimating causal effects

- Practical applications of DID in AI and ML

Day 12: Nonlinear and Nonparametric Econometrics

- Nonlinear regression models and their applications

- Kernel regression and local linear regression

- Semiparametric and nonparametric methods in econometrics

Day 13: Bayesian Econometrics

- Introduction to Bayesian econometrics

- Bayesian regression and its advantages over classical approaches

- Markov Chain Monte Carlo (MCMC) methods for Bayesian estimation

Day 14: Project: Integrating Econometrics into an AI System

- Hands-on project to apply the advanced econometric techniques learned

- Identifying appropriate econometric methods for a complex AI problem

- Implementing the econometric models and integrating them into an AI system

- Evaluating the performance and interpreting the results

WEEK 7 AND 8
Week 7: Python Programming for AI

Day 1: Introduction to Python for AI

- Setting up a Python environment for AI development

- Basic syntax and data types in Python

- Using Jupyter Notebooks for AI projects

Day 2: Data Manipulation with Pandas

- Introduction to the Pandas library

- Data manipulation and cleaning techniques

- Handling missing values and data normalization

Day 3: Data Visualization with Matplotlib and Seaborn

- Introduction to Matplotlib and Seaborn

- Basic plotting techniques for data visualization

- Creating informative and interactive plots

Day 4: Data Analysis with NumPy

- Introduction to the NumPy library

- Fundamental operations and functions for numerical computations

- Using NumPy for data analysis and scientific computing

Day 5: Machine Learning with Scikit-Learn

- Introduction to the Scikit-Learn library

- Supervised and unsupervised learning algorithms

- Implementing machine learning models with Scikit-Learn

Day 6: Project: Building a Simple AI Application

- Hands-on project to apply the Python skills learned so far

- Choosing a suitable AI problem and implementing a solution

- Preprocessing data and training a machine learning model

- Evaluating the performance and interpreting the results

Week 8: Advanced Coding Essentials for AI

Day 7: Data Structures and Algorithms for AI

- Understanding fundamental data structures: arrays, linked lists, stacks, and queues

- Basic algorithms for searching, sorting, and graph traversal

- Applications of data structures and algorithms in AI

Day 8: Graph Algorithms for AI

- Introduction to graph theory and its applications in AI

- Basic graph algorithms: BFS, DFS, Dijkstra's, and Floyd-Warshall

- Implementing graph algorithms in Python

Day 9: SQL for Handling Databases

- Introduction to SQL and its importance in AI

- Basic SQL syntax and data manipulation

- Creating and querying databases with SQL

Day 10: Advanced SQL Techniques

- Advanced SQL queries: joins, subqueries, and window functions

- Handling database transactions and error handling

- Using SQL for data analysis and reporting

Day 11: Database Management Systems for AI

- Understanding database management systems (DBMS) like MySQL, PostgreSQL, and MongoDB

- Choosing the right DBMS for an AI project

- Managing and querying databases with different DBMS

Day 12: Project: Integrating SQL into an AI System

- Hands-on project to apply the SQL skills learned so far

- Identifying a suitable AI problem and integrating SQL into the solution

- Preprocessing data and querying databases for AI tasks

- Evaluating the performance and interpreting the results

Day 13: Advanced Python Libraries for AI

- Introduction to advanced Python libraries: TensorFlow, PyTorch, and Keras

- Using these libraries for deep learning and neural networks

- Implementing complex AI models with these libraries

Day 14: Project: Building a Complex AI Application

- Hands-on project to apply the advanced Python skills learned

- Choosing a complex AI problem and implementing a solution

- Preprocessing data, training models, and integrating multiple AI components

- Evaluating the performance and interpreting the results

Month 3

WEEK 9 AND 10

Week 9: Exploratory Data Analysis (EDA) in AI

Day 1: Introduction to Exploratory Data Analysis (EDA)

- What is EDA and why is it important in AI?

- Understanding the EDA process and its role in the AI/ML workflow

- Importance of EDA for data-driven decision making

Day 2: Data Cleaning and Preprocessing

- Handling missing values: imputation techniques and strategies

- Dealing with outliers and anomalies in the data

- Encoding categorical variables for machine learning models

Day 3: Univariate and Bivariate Analysis

- Analyzing the distribution of individual variables

- Visualizing and interpreting univariate statistics

- Exploring relationships between pairs of variables

Day 4: Multivariate Analysis

- Identifying and visualizing relationships among multiple variables

- Correlation analysis and understanding correlation matrices

- Techniques for dimensionality reduction (e.g., PCA, t-SNE)

Day 5: Exploratory Visualization Techniques

- Choosing the right visualization for the task at hand

- Creating informative and visually appealing plots

- Effective use of color, layout, and annotations

Day 6: Handling Imbalanced Datasets

- Understanding the challenges of imbalanced datasets

- Techniques for addressing class imbalance (e.g., oversampling, undersampling)

- Evaluating model performance on imbalanced data

Day 7: Project: Conducting EDA on a Real-World Dataset

- Hands-on project to apply the EDA concepts learned so far

- Selecting a suitable dataset and defining the problem statement

- Performing a comprehensive EDA, including data cleaning, visualization, and analysis

- Communicating the insights gained from the EDA process

Week 10: Feature Engineering for AI

Day 8: Introduction to Feature Engineering

- What is feature engineering and why is it important in AI?

- Understanding the feature engineering process and its impact on model performance

- Identifying relevant features for a given problem

Day 9: Feature Transformation and Scaling

- Techniques for feature transformation (e.g., log transformation, Box-Cox transformation)

- Standardization and normalization of features

- Handling high-cardinality categorical features

Day 10: Feature Selection Techniques

- Filter-based feature selection (e.g., correlation, mutual information)

- Wrapper-based feature selection (e.g., recursive feature elimination)

- Embedded feature selection (e.g., Lasso, Ridge regression)

Day 11: Feature Engineering for Tabular Data

- Creating new features from existing ones (e.g., binning, discretization)

- Handling temporal and spatial features

- Incorporating domain knowledge into feature engineering

Day 12: Feature Engineering for Text Data

- Techniques for text preprocessing (e.g., tokenization, stemming, lemmatization)

- Representing text data as numerical features (e.g., bag-of-words, TF-IDF)

- Advanced text feature engineering (e.g., word embeddings, named entity recognition)

Day 13: Feature Engineering for Image and Time Series Data

- Extracting features from image data (e.g., edge detection, texture analysis)

- Feature engineering for time series data (e.g., lags, rolling windows, feature engineering)

- Incorporating domain knowledge for specialized data types

Day 14: Project: Applying Feature Engineering to an AI Problem

- Hands-on project to apply the feature engineering concepts learned

- Selecting a suitable dataset and defining the problem statement

- Performing comprehensive feature engineering and evaluating its impact on model performance

- Communicating the feature engineering process and its outcomes

WEEK 11 AND 12

Week 11: Classic Supervised Machine Learning Algorithms

Day 1: Introduction to Classic Machine Learning

- Overview of classic ML algorithms and their role in the AI ecosystem

- Supervised, unsupervised, and semi-supervised learning

- Importance of classic ML in modern AI applications

Day 2: Linear Regression

- Understanding the linear regression model

- Gradient descent and normal equation for model training

- Evaluating model performance and interpreting coefficients

Day 3: Logistic Regression

- Introduction to logistic regression for classification problems

- Sigmoid function and probability interpretation

- Regularization techniques to prevent overfitting

Day 4: Decision Trees

- Fundamentals of decision tree learning

- Entropy, information gain, and the ID3 algorithm

- Handling continuous and categorical features

Day 5: Ensemble Methods: Bagging and Boosting

- Ensemble learning and its advantages

- Bagging algorithms: Random Forest

- Boosting algorithms: AdaBoost and Gradient Boosting

Day 6: Support Vector Machines (SVMs)

- Intuition behind SVMs and the concept of margins

- Kernel functions and their role in SVM

- Handling non-linear and high-dimensional data with SVMs

Day 7: Project: Implementing Classic ML Algorithms

- Hands-on project to apply the classic ML algorithms learned

- Choosing an appropriate algorithm for a given problem

- Preprocessing data, training the model, and evaluating performance

- Interpreting the results and communicating the insights

Week 12: Classic Unsupervised Machine Learning Algorithms

Day 8: K-Means Clustering

- Understanding the K-Means clustering algorithm

- Choosing the optimal number of clusters

- Handling different types of data and distance metrics

Day 9: Hierarchical Clustering

- Agglomerative and divisive hierarchical clustering

- Dendrograms and their interpretation

- Applications of hierarchical clustering

Day 10: Principal Component Analysis (PCA)

- Intuition behind PCA and its use in dimensionality reduction

- Calculating principal components and explained variance

- Applying PCA for data visualization and feature extraction

Day 11: Anomaly Detection

- Unsupervised anomaly detection techniques

- Isolation Forest and One-Class SVM

- Practical applications of anomaly detection in AI

Day 12: Gaussian Mixture Models (GMMs)

- Understanding the GMM algorithm and its assumptions

- Expectation-Maximization (EM) algorithm for GMM training

- Applications of GMMs in clustering and density estimation

Day 13: Recommender Systems

- Content-based and collaborative filtering recommender systems

- Matrix factorization techniques for recommendation

- Evaluating the performance of recommender systems

Day 14: Project: Implementing Classic Unsupervised ML Algorithms

- Hands-on project to apply the classic unsupervised ML algorithms learned

- Choosing an appropriate algorithm for a given problem

- Preprocessing data, training the model, and evaluating performance

- Interpreting the results and communicating the insights

Month 4

WEEK 13 AND 14
Week 13: Advanced Ensemble Methods and Neural Networks

Day 1: Advanced Ensemble Methods
- Understanding the limitations of classic ensemble methods
- Advanced ensemble methods: Random Forest, Gradient Boosting, and Stacking
- Techniques for improving ensemble performance

Day 2: Neural Networks (NNs) for Classification and Regression
- Introduction to neural networks and their architecture
- Understanding the backpropagation algorithm
- Implementing neural networks for classification and regression tasks

Day 3: Hyperparameter Tuning for Neural Networks
- Importance of hyperparameter tuning for neural networks
- Techniques for hyperparameter tuning: grid search, random search, and Bayesian optimization
- Practical applications of hyperparameter tuning

Day 4: Transfer Learning and Pre-trained Models
- Understanding the concept of transfer learning
- Using pre-trained models for specific tasks
- Techniques for fine-tuning pre-trained models

Day 5: Advanced Neural Network Architectures
- Understanding advanced neural network architectures: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks
- Applications of these architectures in various domains

Day 6: Project: Implementing Advanced Ensemble Methods and Neural Networks
- Hands-on project to apply the advanced ensemble methods and neural networks learned
- Choosing an appropriate algorithm for a given problem
- Preprocessing data, training the model, and evaluating performance
- Interpreting the results and communicating the insights

Week 14: Advanced Topics in Machine Learning

Day 7: Reinforcement Learning
- Understanding the basics of reinforcement learning
- Markov Decision Processes (MDPs) and the Bellman equation
- Implementing reinforcement learning algorithms

Day 8: Generative Adversarial Networks (GANs)
- Understanding the concept of GANs
- Generative and discriminative models
- Techniques for training GANs

Day 9: Autoencoders and Variational Autoencoders (VAEs)
- Understanding the concept of autoencoders
- Variational autoencoders and their applications
- Techniques for training autoencoders and VAEs

Day 10: Natural Language Processing (NLP) with Deep Learning
- Understanding the basics of NLP
- Deep learning techniques for NLP: word embeddings, recurrent neural networks, and attention mechanisms
- Implementing NLP models for text classification and language translation

Day 11: Computer Vision with Deep Learning
- Understanding the basics of computer vision

- Deep learning techniques for computer vision: convolutional neural networks and object detection
- Implementing computer vision models for image classification and object detection

Day 12: Advanced Techniques for Handling Imbalanced Datasets
- Understanding the challenges of imbalanced datasets
- Techniques for handling imbalanced datasets: oversampling, undersampling, and cost-sensitive learning
- Practical applications of these techniques

Day 13: Advanced Techniques for Handling High-Dimensional Data
- Understanding the challenges of high-dimensional data
- Techniques for handling high-dimensional data: dimensionality reduction, feature selection, and regularization
- Practical applications of these techniques

Day 14: Project: Implementing Advanced Techniques in Machine Learning
- Hands-on project to apply the advanced techniques learned
- Choosing an appropriate technique for a given problem
- Preprocessing data, training the model, and evaluating performance
- Interpreting the results and communicating the insights

WEEK 15 AND 16

Week 15: Deep Learning Fundamentals

Day 1: Introduction to Deep Learning
- What is Deep Learning and how does it differ from traditional Machine Learning?
- Overview of the history and evolution of Deep Learning
- Applications of Deep Learning in various domains

Day 2: Fully Connected Neural Networks
- Understanding the structure and components of a fully connected neural network
- Activation functions and their role in neural networks
- Backpropagation algorithm for training neural networks

Day 3: Optimization Techniques for Neural Networks
- Gradient-based optimization methods: Stochastic Gradient Descent, Momentum, and Adam
- Regularization techniques: L1/L2 regularization, Dropout, and Early Stopping
- Batch Normalization and its impact on training

Day 4: Convolutional Neural Networks (CNNs)
- Intuition behind convolutional layers and their operation
- Pooling layers and their role in CNNs
- Architectural design of CNNs and their applications in computer vision

Day 5: Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs)
- Understanding the need for RNNs and their structure
- Vanishing and exploding gradient problems in RNNs
- LSTM units and their ability to capture long-term dependencies

Day 6: Project: Implementing a Simple Deep Learning Model
- Hands-on project to apply the deep learning concepts learned so far
- Choosing an appropriate deep learning architecture for a given problem
- Preprocessing data, training the model, and evaluating performance
- Interpreting the results and communicating the insights

Week 16: Advanced Deep Learning Architectures

Day 7: Generative Adversarial Networks (GANs)
- Understanding the concept of generative models and their applications
- Discriminator and generator networks in GANs
- Techniques for training stable and effective GANs
Day 8: Autoencoders and Variational Autoencoders (VAEs)
- Autoencoder architecture and its use in dimensionality reduction
- Variational Autoencoders and their ability to generate new data
- Applications of autoencoders and VAEs in deep learning

Day 9: Transformers and Attention Mechanisms
- Limitations of RNNs and the need for Transformers
- Attention mechanisms and their role in Transformers
- Implementing Transformer-based models for NLP tasks

Day 10: Transfer Learning and Fine-Tuning
- Understanding the concept of transfer learning
- Techniques for fine-tuning pre-trained deep learning models
- Practical applications of transfer learning in deep learning
Day 11: Reinforcement Learning and Deep Reinforcement Learning
- Introduction to Reinforcement Learning (RL) and its key components
- Combining RL with deep learning: Deep Reinforcement Learning
- Implementing RL algorithms for solving complex problems

Day 12: Deployment and Optimization of Deep Learning Models
- Techniques for deploying deep learning models in production
- Optimizing deep learning models for inference and deployment
- Addressing challenges in real-world deep learning applications
Day 13: Ethical Considerations in Deep Learning
- Understanding the importance of ethical AI
- Bias, fairness, and interpretability in deep learning models
- Strategies for responsible development and deployment of deep learning

Day 14: Project: Implementing an Advanced Deep Learning Model
- Hands-on project to apply the advanced deep learning concepts learned
- Choosing an appropriate deep learning architecture for a complex problem
- Preprocessing data, training the model, and evaluating performance
- Interpreting the results, communicating the insights, and addressing ethical considerations

Month 5

WEEK 17 AND 18
Week 17: Introduction to Transfer Learning

Day 1: What is Transfer Learning?
- Understanding the concept of transfer learning
- Advantages of transfer learning over training from scratch
- Scenarios where transfer learning is beneficial

Day 2: Transfer Learning Approaches
- Feature-based transfer learning
- Fine-tuning pre-trained models
- Domain adaptation and its techniques

Day 3: Transfer Learning Strategies
- Choosing the right pre-trained model
- Freezing and unfreezing layers during fine-tuning
- Techniques for adapting pre-trained models to new tasks

Day 4: Transfer Learning for Computer Vision
- Using pre-trained models for image classification
- Adapting pre-trained models for object detection and segmentation
- Techniques for fine-tuning and evaluating CV models

Day 5: Transfer Learning for Natural Language Processing
- Using pre-trained language models (e.g., BERT, GPT)
- Fine-tuning language models for text classification and generation
- Techniques for adapting NLP models to specific domains

Day 6: Transfer Learning for Time Series Data
- Challenges and considerations in time series transfer learning
- Adapting pre-trained models for time series forecasting
- Techniques for fine-tuning and evaluating time series models

Day 7: Project: Implementing Transfer Learning for a Computer Vision Task
- Hands-on project to apply transfer learning concepts in computer vision
- Selecting a pre-trained model and fine-tuning it for a specific task
- Evaluating the performance and comparing it to training from scratch
- Communicating the insights and lessons learned

Week 18: Advanced Topics in Transfer Learning

Day 8: Transfer Learning for Small Datasets
- Challenges of training deep learning models on small datasets
- Techniques for leveraging transfer learning with limited data
- Strategies for data augmentation and meta-learning

Day 9: Multi-Task and Continual Learning
- Understanding the concept of multi-task learning
- Techniques for training models to solve multiple tasks simultaneously
- Continual learning and overcoming catastrophic forgetting

Day 10: Domain Adaptation and Generalization
- Challenges of domain shift and the need for domain adaptation
- Techniques for adapting models to new domains (e.g., adversarial training)
- Strategies for improving model generalization across domains

Day 11: Interpretability and Explainability in Transfer Learning

- Importance of interpretability and explainability in deep learning
- Techniques for interpreting and explaining transfer learning models
- Ethical considerations in the use of interpretable transfer learning

Day 12: Transfer Learning for Edge and Mobile Devices
- Challenges and considerations in deploying deep learning on edge devices
- Techniques for model compression and efficient inference
- Strategies for on-device transfer learning and personalization

Day 13: Transfer Learning in Reinforcement Learning
- Applying transfer learning to reinforcement learning problems
- Techniques for leveraging pre-trained models in RL environments
- Strategies for accelerating RL training through transfer learning

Day 14: Project: Implementing Transfer Learning for a Natural Language Processing Task
- Hands-on project to apply transfer learning concepts in NLP
- Selecting a pre-trained language model and fine-tuning it for a specific task
- Evaluating the performance and comparing it to training from scratch
- Communicating the insights and lessons learned, including interpretability aspects

WEEK 19 AND 20
Week 19: MLOps and Deployment Models

Day 1: Introduction to MLOps
- What is MLOps and why is it important?
- Key components of the MLOps lifecycle
- Challenges in deploying and maintaining ML models in production

Day 2: Deployment Models for AI Applications
- On-premises deployment
- Cloud-based deployment
- Hybrid deployment
- Factors to consider when choosing a deployment model

Day 3: Containerization and Orchestration
- Understanding Docker and container-based deployment
- Kubernetes and its role in MLOps
- Deploying and managing ML models using Kubernetes

Day 4: Serverless Deployment of AI Models
- Serverless computing and its advantages
- Deploying ML models on serverless platforms (e.g., AWS Lambda, Azure Functions)
- Considerations and best practices for serverless ML deployments

Day 5: Model Serving Architectures
- Client-server model serving
- Batch inference vs. real-time inference
- Serving multiple models and versions

Day 6: Model Monitoring and Observability
- Monitoring model performance in production
- Detecting data drift and model drift
- Techniques for improving model observability

Day 7: Project: Implementing an MLOps Deployment Pipeline
- Hands-on project to apply the MLOps deployment concepts learned
- Choosing an appropriate deployment model for a given AI application
- Containerizing the model and deploying it using Kubernetes or a serverless platform
- Implementing monitoring and observability mechanisms

Week 20: Continuous Integration and Continuous Deployment (CI/CD) in AI

Day 8: Introduction to CI/CD in AI
- Understanding the principles of Continuous Integration and Continuous Deployment
- Challenges and considerations in applying CI/CD to AI/ML projects

Day 9: CI/CD Tooling for AI
- Popular CI/CD tools and their integration with AI/ML workflows
- Configuring CI/CD pipelines for training, testing, and deploying ML models

Day 10: Versioning and Reproducibility in AI
- Importance of versioning in the AI/ML lifecycle
- Tools and techniques for versioning data, models, and experiments
- Ensuring reproducibility of AI/ML workflows

Day 11: Testing and Validation in AI/ML Pipelines
- Unit testing, integration testing, and end-to-end testing for AI/ML
- Techniques for data validation and model validation
- Automating testing in CI/CD pipelines

Day 12: Deployment Strategies for AI/ML
- Blue-green deployment
- Canary releases
- A/B testing and feature flags

Day 13: Monitoring and Alerting in AI/ML Pipelines
- Monitoring model performance and data quality in production
- Setting up alerts and notifications for anomalies and failures
- Integrating monitoring and alerting into CI/CD workflows

Day 14: Project: Implementing a CI/CD Pipeline for an AI/ML Application
- Hands-on project to apply the CI/CD concepts learned
- Designing and configuring a CI/CD pipeline for training, testing, and deploying an AI/ML model
- Incorporating versioning, reproducibility, and deployment strategies
- Implementing monitoring and alerting mechanisms

Month 6

WEEK 21 AND 22
Week 21: Capstone AI Project - Part 1

Day 1: Capstone Project Introduction
- Overview of the capstone project and its objectives
- Defining the problem statement and scope of the project
- Forming teams and allocating responsibilities

Day 2: Data Exploration and Preprocessing
- Conducting exploratory data analysis (EDA) on the project dataset
- Cleaning and preprocessing the data for model training
- Identifying relevant features and engineering new ones

Day 3: Baseline Model Development

- Selecting appropriate machine learning or deep learning algorithms
- Implementing a baseline model and evaluating its performance
- Identifying areas for improvement and optimization

Day 4: Feature Engineering and Model Optimization
- Applying advanced feature engineering techniques
- Tuning hyperparameters and optimizing the model
- Evaluating the improved model performance

Day 5: Ensemble Methods and Advanced Techniques
- Exploring the use of ensemble methods to boost model performance
- Incorporating advanced techniques like transfer learning or domain adaptation
- Evaluating the impact of these techniques on the project

Day 6: Model Evaluation and Interpretation
- Comprehensive evaluation of the final model's performance
- Interpreting the model's predictions and understanding its behavior
- Identifying potential biases or ethical concerns

Day 7: Project Progress Presentation
- Teams present their progress on the capstone project
- Receive feedback and guidance from instructors and peers
- Discuss challenges faced and plans for the next phase

Week 22: Capstone AI Project - Part 2

Day 8: MLOps and Deployment Considerations
- Designing the deployment architecture for the AI system
- Implementing CI/CD pipelines for model training and deployment
- Addressing scalability, monitoring, and maintenance requirements

Day 9: Documentation and Reporting
- Documenting the project's objectives, methodology, and findings
- Preparing a comprehensive project report and presentation
- Ensuring the project's reproducibility and knowledge sharing

Day 10: Ethical Considerations and Responsible AI
- Identifying and addressing potential ethical concerns in the project
- Incorporating principles of responsible AI development
- Discussing the project's impact and societal implications

Day 11: Final Project Presentation - Part 1
- Teams present their capstone project to the class
- Showcase the end-to-end AI solution and its key components
- Receive feedback and questions from the audience

Day 12: Final Project Presentation - Part 2
- Continuation of the final project presentations
- Teams respond to questions and defend their work
- Instructors and peers provide comprehensive feedback

Day 13: Project Reflection and Lessons Learned
- Teams reflect on the challenges, successes, and key takeaways
- Discuss the skills and knowledge gained throughout the course
- Identify areas for further learning and professional development

Day 14: Graduation and Celebration
- Celebration of the successful completion of the course
- Awarding of certificates and recognition of outstanding achievements
- Networking and sharing of future plans and aspirations