Government of Pakistan

National Vocational and Technical Training Commission

Prime Minister's Hunarmand Pakistan Program

"Skills for All"



Course Contents / Lesson Plan

Course Title: Artificial Intelligence (Machine Learning & Deep Learning)

Duration: 3 Months

Trainer Name	
Course Title	Artificial Intelligence (Machine Learning & Deep Learning)
Objective of Course	Employable skills and hands on practice for Artificial Intelligence, including specialization in Natural Language Processing (NLP) and Microsoft Azure Al Associate
	The aim for the team of staff responsible for delivery of the advanced IT curriculum is to provide knowledge and develop skills related to the IT. The course will allow participants to gain a comprehensive understanding of all the aspects. It will also develop the participant's ability to act in a professional and responsible manner.
	Teaching staff will provide the technical knowledge and abilities required to solve tasks and problems that are goal-oriented. They will use participant-centered, practically oriented methods. They will also develop a program of practical assessment that reflects the learning outcomes stated in the curriculum. Trainees of the IT curriculum will also develop their willingness and ability as individuals to clarify issues, as well as think through and assess development opportunities.
	Teaching staff will also support trainees in developing characteristics such as self-reliance, reliability, responsibility, a sense of duty and a willingness and ability to criticize and accept criticism well and to adapt their future behavior accordingly.
	Teaching staff also use the IT curriculum to address the development of professional competence. Trainees will acquire the ability to work in a professional environment. By the end of this course, the trainees should gain the following competencies:
	Understanding of core concepts of artificial intelligence and machine learning State of the art machine learning techniques Hands-on exposure to exploratory data analysis Practical exposure to model design, evaluation Familiarity with tools and libraries such as scikit learn,

After taking this course, you will be familiar with the fundamentals **Learning Outcome of the** of Artificial Intelligence. You will gain practical experience in Course applying AI for problem solving, and will develop a deep understanding of the core concepts by implementing solutions to real world problems. By the end of this course, the trainees should gain the following competencies: Understanding of core concepts of artificial intelligence and machine learning State of the art machine learning techniques Hands-on exposure to exploratory data analysis Practical exposure to model design, evaluation Familiarity with tools and libraries such as scikit learn, pandas numpy, tensorflow, pytorch and keras After the specialization in NLP, you will be comfortable using TensorFlow pipelines for NLP at the end of the course. Moreover, You will learn to build your own models which will extract information from textual data. You will learn text processing fundamentals, including text normalization, stemming and lemmatization. You will learn about different evaluation metrics for models trained for NLP tasks. You will learn to make a part of speech (POS) tagging model. You will learn about named entity recognition. You will learn advanced techniques including word embeddings, deep learning (DL) techniques. You will learn how to deploy a NLP model Moreover, you will learn not only all these skills but also learn to use Microsoft Azure API for Machine and Deep Learning for numerical, image and text data. **Course Execution Plan** Total Duration of Course: 3 Months Class Hours: 4 Hours per day Theory: 20% Practical: 80% **Companies Offering Jobs** 1. Careem in the respective trade 2. Afiniti 3. Addo.ai 4. Arbisoft 5. I2c 6. Xavor 7. Fiverivers Technologies 8. Confiz 9. Crossover 10. NetSol 11. Research institutes 12. All Private Institutes who have an ML department **Job Opportunities** Al is the buzzword of the century, attracting attention across industries, motivating changes in products as well as services. It is the very nature of the subject that makes its applications

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in multiple domains. Whether you belong to a technical background or not, chances are that AI can make your job easier, and push it in the right direction. Dive in to develop an understanding of the core concepts, while gaining hands on experience and training from the industry's finest. Trained resources can find work as one of the following roles:

- Al Associate Engineer
- Machine Learning associate analyst
- Assistant Data Analyst
- Research Assistant

No of Students	25
Learning Place	Classroom / Lab
Instructional Resources / Reference Material	 Linux: Learn Linux Shell Scripting – Fundamentals of Bash 4.4 [Sebastiaan Tammer - Packt Publishing Ltd.] Sams Teach Yourself Shell Programming in 24 Hours [Second Edition , Sams Publishing] Applied Data Science – (Chapter 01) [Ian Langmore & Daniel Krasner] Linux Tutorial – Basic Command Line https://www.youtube.com/watch?v=cBokz0LTizk
	 Python: Learning Python – 2nd Edition (Ch:12: OOP in Python) [B. Nagesh Rao, CyberPlus Infotech Pvt. Ltd.] Python for Everybody [Dr. Charles R. Severance] Python: A Simple Tutorial [Matt Huenerfauth, University of Pennsulvania, USA] Smarter Way to Learn Python [Mark Mayers] A Python Book: Beginning Python, Advanced Python, and Python Exercises [Dave Kuhlman] Mastering Object-Oriented Python [Second Edition, Steven F. Lott, Pack Publishing Ltd.] Python Official Documentation https://docs.python.org/3/ Descriptive Statistics and Probability: Probability for Machine Learning [Jason Brownlee] Making Sense of Data: A Practical Guide to Exploratory Data Analysis and Data Mining (Ch: 02) [Second Edition, Glenn J. Myatt & Wayne P. Johnson, WILEY] Practical Statistics for Data Scientists [Second Edition, Peter Bruce, Andrew Bruce, and Peter Gedeck, O'REILLY]

Exploratory Data Analysis: Numpy Python for Data Analysis (Ch:04, Appendix A: Advanced Numpy) [Second Edition, Wes McKinney, O'REILLY] Numpy Official Documentation https://numpy.org/doc/1.24/ Pandas Pandas 1.x Cookbook [Second Edition, Matt Harrison & Theodore Petrou, Pack Publishing Ltd. Python for Data Analysis (Ch:05, 07, 10, 12) [Second Edition, Wes McKinney, O'REILLY] Hands-on Exploratory Data Analysis with Python (Ch: 04, 06) [Suresh Kumar Mukhiya & Usman Ahmed, Pack Publishing Ltd.] Pandas Official Documentation https://pandas.pydata.org/docs/ Matplotlib Pandas 1.x Cookbook (Ch:13) [Second Edition, Matt Harrison & Theodore Petrou, Pack Publishing Ltd.] Hands-on Exploratory Data Analysis with Python (Ch: 04, 06) [Suresh Kumar Mukhiya & Usman Ahmed, Pack Publishing Ltd.] Matplotlib Official Documentation https://matplotlib.org/stable/index.html Seaborn Pandas 1.x Cookbook (Ch:13) [Second Edition, Matt Harrison & Theodore Petrou, Pack Publishing Ltd. Python for Data Analysis (Ch:09) [Second Edition, Wes McKinney, O'REILLY]

 Seaborn Official Documentation https://seaborn.pydata.org/

Machine Learning:

- Machine Learning by Andrew NG (Also available freely on Youtube) https://www.coursera.org/collections/machine-learning
- Machine Learning: An Algorithmic Perspective [Second Edition, Stephen Marsland, CRC Press]
 Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow

[Third Edition, Aurélien Géron, O'REILLY]

- XGBoost with Python [Jason Brownlee]
- Learn TensorFlow 2.0
 [Pramod Singh & Avinash Manure, Apress]

Natural Language Processing:

- Speech and Language Processing
- [Third Edition, Dan Jurafsky, James H. Martin]
- Deep Learning for Natural Language Processing [Jason Brownlee]
- Natural Language Processing Cookbook
 [Krishna Bhavsar, Naresh Kumar, & Pratap Dangeti,
 Pack Publishing Ltd.]

Deep Learning:

- Deep Learning by Andrew NG (Also available freely on Youtube)
- •https://www.coursera.org/learn/neural-networks-deep-learning
- Deep Learning with Python [Jason Brownlee]
- Deep Learning for Time Series Forecasting [Jason Brownlee]
- Long Short-Term Memory Networks with Python [Jason Brownlee]
- [Jason Brownlee]
- Dive into Deep Learning [Aston Zhang, Zachary C. Lipton, Mu Li, and Alexander J. Smola]

Microsoft Azure Machine Learning:

- Mastering Azure Machine Learning: Execute Large-Scale End-to-end Machine Learning with Azure [Second Edition, Christopher Korner and Marcel Alsdorf, Packt Publishing Ltd.]
- Microsoft Azure Al Fundamentals Training

https://learn.microsoft.com/enus/training/paths/prepare-teach-ai-900fundamentals-academic-programs/

- Microsoft Azure Al Associate Training
 https://learn.microsoft.com/en us/training/paths/prepare-teach-ai-102-microsoft design-implement-azure/
- Microsoft Learn for Educators Program
 https://learn.microsoft.com/en-us/training/educator-center/programs/msle/

Software Download:

Anaconda

https://www.anaconda.com/

VSCode

https://code.visualstudio.com/

- PyCharm (Community Edition) https://www.jetbrains.com/pycharm/
- PyTorch https://pytorch.org/get-started/locally/
- TensorFlow 2.0 https://www.tensorflow.org/install

Week 1 Intro	duction	Day 1 Hour#		
		1	 Introduction to AI Motivational Lecture (For further detail please see Page No: 3& 4) 	• Task 1
		Hour# 2	Job marketCourse ApplicationsWork ethics	• Task 3-25
		House	Survey of career opportunities Survey of industry requirements for each career path	Details may be seen at Annexure-I
	x Shell	Hour#	PyCharm, etc.)	-
Scrip Fund	oting damentals	Day 2 Hour#	Introduction to Debian Basic Commands: pwd, cd, ls, cat, sudo, man, redirection, mkdir, rm, rmdir, cp, mv	
		2	•file, reading, cat, more, less, head, alias,	-
		3	•shutdown, restart, touch, nano, bash, sh, chmod, ps, kill, dpkg	_
		Hour#	upgrade•Environment	-
Pyth Fund	on damentals	# 1	Values, expressions, and statementsNumbers, Booleans, StringsOperators, variables and keywords	
		Hour # 2,3	•String operations	
		Hour # 4	•Input and Type casting •Comments	
		Day 4 Hour # 1 & 2	Data Structures • Lists • Tuples	
		Hour # 3 & 4	• Sets	
			Conditional Execution •If, elif, and else statements	

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Neek 2 Python Fundamentals Day 1 Hour# * Motivational Lecture (For further detail please see Page No: 38.4) * Task 26-27 * Task 49-51			1		1
Week 2 Python Fundamentals Day 1 Hour# • Motivational Lecture (For further detail please see Page No: 3& 4) Hour # • Functions and variable scope • Lambda expression Map and Filter • Inner/Nested functions Python Day 2 Hour# • Functions and variable scope • Lambda expression Map and Filter • Inner/Nested functions Implementation of OOP Principals in Python Day 2 Hour# • Classes and Objects Instance Variables and Methods • Class Variables and Functions Constructors and Destructors Hour# • Inheritance Multiple Inheritance • Hierarchical Inheritance •					
# 3 & 4 enumerate Nested loops List comprehension elterators and Iterables • Day 1 Hour# 2,3 Implementation of OOP Principals in Python Implementation of Planuari of Principals in Python Implementation of Principals in Principals says 49- Implementation of Principals in Principals says 49- Implementation of Principals in Principals says 49- Implementation of Principals in Python Implementation of Principals in Python Implementation of Principals says 49- Implementation of Princi				Conditional (Ternary) Expression	
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Hour# • Functions 2, 3 Hour# Functions Functions Functions and variable scope Lambda expression Map and Filter Inner/Nested functions	TTOOK 2	1 -	1 1001#	`	■ Tack 26-
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Details may be Deta			Hour#	Functions	
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Implementation of OOP Principals in Python				Lambda expression	51
Implementation of OOP Principals in Python Day 2 Hour# Classes and Objects Instance Variables and Methods Class Variables and Functions Constructors and Destructors				<u> </u>	
The properties of OOP Principals in Python Day 2 Hour#					
Implementation of OOP Principals in Python 4 Day 2 Hour# • Classes and Objects Instance Variables and Methods • Class Variables and Functions Constructors and Destructors Hour# • Inheritance Multilevel Inheritance • Hierarchical Inheritance, Method Resolution Order Hour# • Access Specifiers: Private, Public, Protected Name Mangling • Inner/Nested Class Association, Aggregation, Composition Day 3 Hour# • Polymorphism and Operator Overloading 1 Hour# • Magic Functions/Dunder Functions 2 Hour# • Dynamic Polymorphism (subclass as base class) Hour# • Abstract Method and Class, Empty Class, Data Class • Keyword Arguments Descriptive Statistics and Probability Day 4 Hour# • Data and its types (structured, Unstructured) • Quantitative data, Numerical, Continuous,			Hour	File Handling	
Implementation of OOP Principals in Python Classes and Objects Instance Variables and Methods Class Variables and Functions Constructors and Destructors Hour# • Inheritance Multiple Inheritance, Method Resolution Order Hour# • Access Specifiers: Private, Public, Protected Name Mangling • Inner/Nested Class Association, Aggregation, Composition Day 3 Hour# • Polymorphism and Operator Overloading 1 Hour# • Magic Functions/Dunder Functions 2 Hour# • Dynamic Polymorphism (subclass as base class) Hour# • Abstract Method and Class, Empty Class, Data Class Keyword Arguments Descriptive Statistics and Prohability Day 4 Hour# • Data and its types (structured, Unstructured) Quantitative data, Numerical, Continuous,			#	Exception Handling	Dotaile may be
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Descriptive Statistics and Probability The expression of the continuous of the cont			Hour#		
Descriptive Statistics and Probability Day 4 Hour# Output Day 4 Hour# Quantitative data, Numerical, Continuous,			4	I •	
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Probability 1, 2 • Quantitative data, Numerical, Continuous,				1	
and Discrete variables			1, 2		
Artificial Intelligence Machine Learning				and Discrete variables	

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	Overview		Qualitative data, Categorical, Nominal,	
			Ordinal, and Binary variables	
		11	Management of Countries Transfers of	
			Measures of Central Tendency	
		#	●Mean, Mode, Median	
		3-4	Marana of Diamanaian	
		, ,	Measures of Dispersion	
		1,2	Variance, Standard deviation	
			Co-efficient of variation, skewness and kurtosis	
			Kurtosis	
		Hour#	Measures of Position	
			•Z-Score, Percentile, Quartile	
		, , ,	- Z Goord, 1 Groomine, Quartine	
Week 3	Descriptive	Day 1 Hour#	Motivational Lecture (For further detail	
	Statistics and	1	please see Page No: 3& 4)	● Task 28-
	Probability	Hour#	,	48
	Overview	2	2 Sandadan Godinolont	
		Hour#	Univariate, bivariate and multivariate plots	
		3	,	
		Hour#	Probability	<u>Details may be</u>
		4	,	<u>seen at</u>
		Day 2 Hour#	Joint, Marginal and Conditional probability	<u>Annexure-I</u>
		1		
		Hour#	Probability Distributions	
		2	•	
		Hour	Discrete and Continuous probability	
		# 3-4		
			Bayesian Probability	
		Day 3 Hour#	Introduction to Numpy	
	Python Support	1		
	Libraries for	Hour#		
	Exploratory Data Analysis	2,3,4	· · · · · · · · · · · · · · · · · · ·	
	- NUMPY		Array Attributes and Methods (reshape, max,	
	TVOIVII 1		min, argmax, argmin, shape, dtype, size,	
			ndim)	
			 Operations on Arrays (copying, append and Insert, Sorting, Removing/Deleting, 	
			Combining/Concatenating, Splitting)	
		Day 4 Hour		
		# 1-2		
			2D array, Logical Selection)	
			Broadcasting	
		Hour	Type Casting	
		# 3-4		
			Divide, Exponentiation)	
			 Universal Array Functions (sqrt, exp, max, 	

	1			T
			sin, etc)	
	- Pandas	Day 5 Hour#	Introduction to Pandas	
		Hour# 2	 Series and DataFrame and Data Input Selection and Indexing (rows, columns, conditional selection, selection of subset of rows and columns, index setting, etc) 	
		Hour# 3	 Operations on DataFrames (head, unique, value counts, applying custom functions, getting column and index names, sorting and ordering, null value check, value replacement, dropping rows and columns, etc) 	
		Hour# 4	,	
Week 4	Python Support Libraries for Exploratory Data	Day 1 Hour#	please see Page No: 3& 4)	
	Analysis - Pandas	Hour# 2	outer, right and left joins)	
	- Seaborn	Hour # 3-4	Discretization and Binning Operations on DataFrames Data output/saving Pandas for Plotting (area, bar, density, hist,	• Task 28-48
		Day 2 Hour#	line, scatter, barh, box, hexbin, kde, and pie plots Introduction to Seaborn	<u>Details may be</u> <u>seen at</u>
		1		<u>Annexure-I</u>
			Distribution Plots •distplot •jointplot (pairplot, rugplot, kdeplot)	
			Categorical Data Plots •factorplot, boxplot, violinplot, stripplot, swarmplot, barplot, countplot	
			Matrix Plots ●Heatmap	
		Day 3 Hour# 1	,	
		Hour# 2,3,4	311 \	
		Day 4 Hour # 1,2	 Supervised machine learning Regression and classification problems Components of supervised machine learning (labeled data, hypothesis, cost function,	
	jal Intelligence Mach	Hour # 3,4	Univariate Linear Regression with Gradient Descent	

	1	In =1	T	T
		Day 5 Hour	9	
		# 1-2	Bessent	
			Without Vectorization	 -
		Hour # 3-4		
Week 5	Machine Learning-I	Day 1 Hour#	Motivational Lecture (For further detail	
		1	please see Page No: 3& 4)	• Task – 51,52
		Hour# 2,3,4	ŭ	,
		Day 2 Hour# 1,2,3, 4	Polynomial Regression	<u>Details may be</u> <u>seen at</u> <u>Annexure-I</u>
		Day 3 Hour# 1,2,3, 4	Logistic Regression (Binary Classification)	
		Day 4 Hour# 1,2,3, 4	Logistic Regression (Multiclass Classification)	
		Day 5 Hour# 1,2,3, 4	Code practice	
Week 6	Natural Language Processing	Day 1 Hour# 1	Motivational Lecture (For further detail please see Page No: 3& 4)	T 50
		Hour# 2	Introduction to Natural Language Processing	● Task 53- 55
		Hour#	Syntax, Semantics, Pragmatics, and	
		3	Discourse	
			NLP curves and future directions	-
		Hour#	Data pre-processing for NLP	
		4	●Introduction to NLTK/SpaCy	Deteile
		D 011 //	Noise removal (stopwords, punctuation, etc)	<u>Details may be</u>
		Day 2 Hour#		seen at
			Word segmentation	<u>Annexure-I</u>
			Stemming Tank normalization	
			Text normalization	
		Hour	Regular expression for string parsing POS tagging	1
		# 2-3	33 3	
		"2-0	or readanta	
			Chunking and Chinking Lemmatization	
			WordNet	
		Hour#		4
		4	Feature Selection and Extraction	
			Document Similarity	
	Machine Learning II	Day 3 Hour#		-
	Indomino Lourning II	1	- Tooking	
		Hour#	Evaluation Metrics	1
		2	Classification and Regression	
		I I	- Jacomodian and Rogrosolon	I .

		Hou # 3-		Dataset imbalance and its remedies (Augmentation)	
		Day 4 Hou 1,2,		Support Vector Machine (SVM)	
		Hou 4		Decision Tree	
		Day 5 Hou	# •	Decision Tree	-
			ır •	Bagging – Random Forest	_
		# 3-	4		-
		Build You	r CV	– Mid-term Exam	
Week 7		Day 1 Hou	~# •	Motivational Lecture (For further detail	
		1		please see Page No: 3& 4)	
		Hou 2,3,		Boosting	● Task 56-64
	Doon Loorning L			P Feed Forward Neural Network	-
	Deep Learning I	1,2,3			
		4	^	Nonlinearity: Activation functions	
				Cross-Entropy	Details may be
				Computational graph and Backpropagation	seen at
				Vanishing and exploding gradients	Annexure-I
				Overfitting, underfitting, dropout regularization	
		Day 3 Hou	~# •		'
		1,2,3		networks using appropriate deep learning API	
		4	'	of choice (TensorFlow, PyTorch, Keras)	
		Day 4 Hou	ır Co	privolutional Neural Network (CNN)	-
				D CNN for image classification	
		Hou # 3-	ır •	1D CNN for text document classification	
		Day 5 Hou	ır •	Code Practice Neural Networks	
		# 1- Hou	ır •	Code Practice Neural Networks	_
		# 3-	_		
Week 8	Deep Learning II	Day 1 Hou	~# •	Motivational Lecture (For further detail	
		1		please see Page No: 3& 4)	
		Hou 2,3,		Recurrent Neural Networks (RNNs)	
		Day 2 Hou 1,2,3	~# •	Long-Short-Term-Memory Networks (LSTM)	
		Day 3 Hou	# •	LSTM Code Practice	-
		Day 4 Hou 1,2,3		Gated Recurrent Unit Networks	

		ID -: -	11	ODU O L D "	1 1
		Day 5	Hour	GRU Code Practice	
			#1,2,3 ,4		
Week 9	Deep Learning II	Day 1	Hour#	Motivational Lecture (For further detail	
liock 5	Doop Loaning II	Juy 1	1	please see Page No: 3& 4)	
			11-	,	-
				Word Embeddings	
			# 2,3,4	Word2vec Operation and BOW	
			2,3,4	Continuous BOW Continuous Clair representations	
		Day 2	Hour#	Continuous Skip-gram Consign and Custom Embadding Training	_
		Day 2	1,2,3,	Gensim and Custom Embedding Training	
			4		
		Day 3	Hour#	Sequence Models	
			1,2,3,	·	
			4		_
		Day 4		Sequence Models	
			1,2,3,		
		D 5	4	• 1 to Many	-
		Day 5		Sequence Models	
			1,2,3, 4	●Many to 1 ●Many to Many	
Week 10	Deep Learning II	Day 1	Hour#		
Week 10	Deep Learning II	Day	1	please see Page No: 3& 4)	• Task 65
			Llauw	,	- Task 05
			Hour# 2,3,4		Details may be
		Day	Hour#		seen at
		2,3	1,2,3,	Attention Mechanism in Models	Annexure-I
	Employable Project		4		
	/ Assignment	Day		Selection of Project, architecture discussion,	
	(2 weeks, 11-12) in	4,5	1,2,3,	preparation.	
	addition of regular		4	Guidelines to the Trainees for selection of	
	classes.			employable project like final year project (FYP).	
	OR			Assignment of Independent project to each	
	On job training (2			Trainee.	
	weeks)			• A project based on trainee's aptitude and	
				acquired skills.	
				Designed by keeping in view the emerging	
				trends in the local market as well as across	
				the globe.	
				The project idea may be based on	
				entrepreneurship.	
				Leading to the successful employment.	
				The duration of the project will be 2 weeks	
				Ideas may be generated via different sites such as:	
				https://1000projects.org/	
				https://nevonprojects.com/	
				https://www.freestudentprojects.com/	
i	1	1	1	,	1

Day 3 Hour Create & Manage Microsoft Azure Al Service # 1-2 •Create an Azure Al resource •Configure diagnostic logging

	Г			
		Hour		
		# 3-4		
	Day 4	Hour		
		# 1-2	Determine a default endpoint for a service	
			Create a resource by using the Azure portal	
			Integrate Azure AI services into a continuous	
			integration/continuous deployment (CI/CD)	
			pipeline	
			Plan a container deployment	
			Implement prebuilt containers in a connected	
			environment	
		Hour	Microsoft Azure Creation of Solutions for Anomaly	
			Detection Content Improvement	
			•Create a solution that uses Anomaly	
			Detector, part of Cognitive Services	
			•Create a solution that uses Azure Content	
			Moderator	
			 Create a solution that uses Personalizer, part 	
			of Cognitive Services	
			•Create a solution that uses Azure Metrics	
			Advisor, part of Azure Applied Al Services	
			•Create a solution that uses Azure Immersive	
			Reader, part of Azure Applied Al Services	
	Day 5	Hour	Microsoft Azure Implementation of Image and	
		# 1-2	Video Processing Solutions	
			Analyze images	
			Extract text from images	
		Hour	Implement image classification and object	
		# 3-4	detection by using the Custom Vision service,	
			part of Azure Cognitive Services	
Week 12	Day 1	Hour#	Motivational Lecture (For further detail	
		1	please see Page No: 3& 4)	
		11	D	
		Hour# 2,3,4	Process videos	
	Day 2		Microsoft Azure Natural Language Processing	● Task 65
			(NLP) Solutions Implementation	
		_	•Analyze text	<u>Details may be</u>
			•Process speech	<u>seen at</u>
			•Translate language	<u>Annexure-I</u>
	Day 3	Hour#		
		1,2,3,		
		4	Create a question answering solution	
	Day 4	Hour#		
		1	model	
		Hour	Microsoft Azure Knowledge Mining Solutions	
			Implementation	
	Day 5	_	Microsoft Azure Conversational Al Solutions	
			Implementation	

Annexure-I

List of Tasks

Tas	Task Title	Description	Wee
k			k
No.			
1.	Installation	Download and install Anaconda3	1
		Install PyTorch	
		Install TensorFlow 2.0	
		Install VSCode	
		Install PyCharm	
2.	Linux	Practice these commands:	1
	Command	pwd, cd, ls, cat, sudo, man, redirection, mkdir, rm, rmdir, cp, mv, file, reading, cat,	
	S	more, less, head, alias, shutdown, restart, touch, nano, bash, sh, chmod, ps, kill,	
		dpkg	
3.	Python		1
		# This program adds two numbers	
		num1 = 1.5	
		num2 = 6.3	
		Tidiliz = 0.5	
		# Add two numbers	
		sum = num1 + num2	
		# Display the sum	
		<pre>print('The sum of {0} and {1} is {2}'.format(num1, num2, sum))</pre>	

```
Python
4.
              # Store input numbers
              num1 = input('Enter first number: ')
              num2 = input('Enter second number: ')
              # Add two numbers
              sum = float(num1) + float(num2)
              # Display the sum
              print('The sum of {0} and {1} is {2}'.format(num1,
              num2, sum))
    Python
5.
              # Python Program to calculate the square root
              # Note: change this value for a different result
              num = 8
              # To take the input from the user
              #num = float(input('Enter a number: '))
              num_sqrt = num ** 0.5
              print('The square root of %0.3f is %0.3f'%(num
              ,num_sqrt))
```

```
Python
6.
                # Find square root of real or complex numbers
                # Importing the complex math module
                import cmath
                num = 1+2j
                # To take input from the user
                #num = eval(input('Enter a number: '))
                num_sqrt = cmath.sqrt(num)
                print('The square root of {0} is {1:0.3f}+{2:0.3f}j'.format(num)
                ,num_sqrt.real,num_sqrt.imag))
     Python
7.
                # Python Program to convert temperature in celsius
                to fahrenheit
                # change this value for a different result
                celsius = 37.5
                # calculate fahrenheit
                fahrenheit = (celsius * 1.8) + 32
                print('%0.1f degree Celsius is equal to %0.1f degree
                Fahrenheit' %(celsius, fahrenheit))
```

```
# Python Program to find the area of triangle

a = 5
b = 6
c = 7

# Uncomment below to take inputs from the user
# a = float(input('Enter first side: '))
# b = float(input('Enter second side: '))
# c = float(input('Enter third side: '))

# calculate the semi-perimeter
s = (a + b + c) / 2

# calculate the area
area = (s*(s-a)*(s-b)*(s-c)) ** 0.5
print('The area of the triangle is %0.2f' %area)
```

```
Python
9.
               # Solve the quadratic equation ax^**2 + bx + c = 0
               # import complex math module
               import cmath
               a = 1
               b = 5
               c = 6
               # calculate the discriminant
               d = (b**2) - (4*a*c)
               # find two solutions
               sol1 = (-b-cmath.sqrt(d))/(2*a)
               sol2 = (-b+cmath.sqrt(d))/(2*a)
               print('The solution are {0} and
               {1}'.format(sol1,sol2))
    Python
10.
               # Taking kilometers input from the user
               kilometers = float(input("Enter value in kilometers: "))
               # conversion factor
               conv_fac = 0.621371
               # calculate miles
               miles = kilometers * conv_fac
               i = 10
11.
    Python
               if (i > 15):
                  print ("10 is less than 15")
                      ("I am Not in if")
```

40	D. 41		T4
12.	Python	i = 20;	1
		if (i < 15):	
		print ("i is smaller than 15")	
		print ("i'm in if Block")	
		else:	
		print ("i is greater than 15")	
		print ("i'm in else Block")	
		print ("i'm not in if and not in else Block")	
40	D (1		
13.	Python	i = 10	1
		if (i == 10):	
		# First if statement	
		if (i < 15):	
		print ("i is smaller than 15")	
		# Nested - if statement	
		-	
		# Will only be executed if statement above	
		# it is true	
		if (i < 12):	
		print ("i is smaller than 12 too")	
		else:	
		print ("i is greater than 15")	
4.4	Duth on		4
14.	Python	i = 20	1
		if (i == 10):	
		print ("i is 10")	
		-	
		elif (i == 15):	
		print ("i is 15")	
		elif (i == 20):	
		print ("i is 20")	
		else:	
		print ("i is not present")	
15.	Python	Exercise on for loops in Python:	1
		https://www.geeksforgeeks.org/python-for-loops/	
16.	Python	Exercise on While loops in Python:	1
4=	 	https://www.geeksforgeeks.org/python-while-loops/	
17.	Python	Exercise on Break statement in Python:	1
40	D (1	https://www.geeksforgeeks.org/python-break-statement/	1
18.	Python	Exercise on Continue statement in Python:	1
10	Dython	https://www.geeksforgeeks.org/python-continue-statement/	1
19.	Python	Exercise on various looping techniques in Python: https://www.geeksforgeeks.org/looping-techniques-python/	1
20.	Python	Exercise on User defined functions in Python:	2
۷٠.	r yu lol i		
		https://www.geeksforgeeks.org/functions-in-python/	

21.	Dython	Exercise on List data type in Python:	1
۷۱.	Python	https://www.programiz.com/python-programming/list	1
22.	Duthon	Exercise on Tuple data type in Python:	1
22.	Python	https://www.programiz.com/python-programming/tuple	1
22	Dython	Exercise on String data type in Python:	1
23.	Python	https://www.programiz.com/python-programming/string	1
24	Dython	Exercise on Set data type in Python:	1
24. Python		https://www.programiz.com/python-programming/set	1
25.	Dython	Exercise on Dictionary data type in Python:	1
25.	Python	https://www.programiz.com/python-programming/dictionary	1
26.	Python	Exercise on Exception Handling in Python:	2
20.	Fyillon	https://www.programiz.com/python-programming/exception-handling	2
27.	Python	Exercise on User defined Exception Handling in Python:	2
21.	Fyillon	https://www.programiz.com/python-programming/user-defined-exception	2
28.	Numpy	Exercise on Numpy create Array Using Python:	3,4
20.	Numpy	https://www.w3schools.com/python/numpy_creating_arrays.asp	3,4
29.	Numpy	Exercise on Numpy Indexing in Array Using Python:	3,4
29.	Numpy	https://www.w3schools.com/python/numpy_array_indexing.asp	3,4
30.	Numpy	Exercise on Numpy Slicing in Array Using Python:	3,4
30.	Numpy	https://www.w3schools.com/python/numpy_array_slicing.asp	3,4
31.	Numpy	Exercise on Numpy Slicing in Array Using Python:	3,4
31.	Numpy	https://www.w3schools.com/python/numpy_data_types.asp	3,4
32.	Numpy	Exercise on Numpy Array coping and viewing :	3,4
32.	Numpy	https://www.w3schools.com/python/numpy_copy_vs_view.asp	3,4
33.	Numpy	Exercise on Numpy Array Shaping:	3,4
55.	Numpy	https://www.w3schools.com/python/numpy_array_shape.asp	3,4
34.	Numpy	Exercise on Numpy Array reshaping :	3,4
J . .	Numpy	https://www.w3schools.com/python/numpy_array_reshape.asp	0,4
35.	Numpy	Exercise on Numpy Array iteration:	3,4
55.	INGILIPY	https://www.w3schools.com/python/numpy_array_iterating.asp	0,4
36.	Numpy	Exercise on Numpy Matrix joining	3,4
50.	INGILIPY	https://www.w3schools.com/python/numpy_array_join Week 4.asp	0,4
37.	Numany	Exercise on Numpy Array splitting	2.4
31.	Numpy	https://www.w3schools.com/python/numpy_array_split.asp	3,4
38.	Numny	Exercise on Numpy Array searching	3,4
30.	Numpy	https://www.w3schools.com/python/numpy_array_search.asp	3,4
39.	Numpy	Exercise on Numpy Array sorting	3,4
59.	Numpy	https://www.w3schools.com/python/numpy_array_sort.asp	3,4
40.	Numpy	Exercise on Numpy Array Random technique	3,4
40.	Numpy	https://www.w3schools.com/python/numpy_random.asp	3,4
41.	Pandas	Exercise on Pandas basics:	3,4
41.	Falluas	https://www.w3schools.com/python/pandas_tutorial.asp	3,4
42.	Pandas	Exercise on Pandas installation:	3,4
4Z.	i aliuas	https://www.w3schools.com/python/pandas_getting_started.asp	J,4
43.	Pandas	Exercise on Pandas Series data	3,4
₽3.	i aliuas	https://www.w3schools.com/python/pandas_series.asp	J,4
44.	Pandas	Exercise on Pandas Data Frame:	3,4
74.	i aliuas	https://www.w3schools.com/python/pandas_dataframes.asp	3,4
45.	Pandas	Exercise on Pandas Open CSV files:	3,4
4 J.	Falluas	https://www.w3schools.com/python/pandas_csv.asp	J.4
	1	https://www.woodhools.com/python/pandas_cov.dop	

https://www.w3schools.com/bython/pandas analyzing.asp 1	46	Dandas	Evereine en Bandes Dete englyzetien:	2.4
48. Pandas Exercise on Pandas Data Cleaning techniques: https://www.w3schools.com/python/pandas_cleaning.asp Exercise on Pandas Data Correlation: https://www.w3schools.com/python/pandas_correlations.asp 49. Stats Perform Mean, Midian and mode: https://www.w3schools.com/python/python ml mean median mode asp 50. Stats Perform Standard Deviation: https://www.w3schools.com/python/python ml mean median mode asp 51. Machine Learning https://www.w3schools.com/python/python ml standard_deviation.asp 52. Machine Learning https://www.daschools.com/python/python ml_standard_deviation.asp 53. Machine Learning https://www.daschools.com/python/python-mython-sklearn-numpy-mist-nandwriting-recognition-matplotilib-a6b31e2b166a https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python 54. Machine Learning https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python 55. Machine Learning https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python 56. Machine Learning https://www.datacamp.com/community/tutorials/decision-tree-classification-python 57. Deep Learning https://www.datacamp.com/community/tutorials/decision-tree-classification-python 58. Deep https://www.datacamp.com/community/tutorials/decision-tree-classification-python-and-r 59. Deep https://www.datacamp.com/community/tutorials-decision-tree-classification-python-and-r 59. Deep https://www.analyticsvidhya.com/blog/2020/07/neural-networks-from-scratch-in-python-and-r 59. Deep https://www.analyticsvidhya.com/blog/2020/07/neural-networks-from-scratch-in-python-and-r 60. Deep https://www.analyticsvidhya.com/blog/2019/08/detailed-guide-7-loss-functions-machine-learning-python-ucode/ 61. Deep https://whon-python-dode/ 62. Zercise on Neural Network: https://www.analyticsvidhya.com/blog/2019/08/detailed-guide-7-loss-functions-machine-learning-python-dode/ 63. Deep https://medium.com/lowards-artificial-intelligence/natural-language-processing-nlp-with-python-lutorial-for-beginners-1	46.	Pandas	Exercise on Pandas Data analyzation:	3,4
https://www.w3schools.com/python/pandas_cleaning.asp Stats Exercise on Pandas Data Correlation: https://www.w3schools.com/python/pandas_correlations.asp Perform Mean, Midlain and mode. 2 Perform Mean, Midlain and mode. 2 Perform Mean, Midlain and mode. 2 Perform Standard Deviation: https://www.w3schools.com/python/python ml_mean_median_mode.asp Perform Standard Deviation: https://www.w3schools.com/python/python ml_mean_median_mode.asp Perform Standard Deviation: https://www.w3schools.com/python/python ml_standard_deviation.asp Perform Notistics Regression https://stackabuse.com/linear-regression-in-python-with-scikit-leam/ Perform Logistics Regression: https://stackabuse.com/linear-regression-using-python-skleam-numpy-mnist-handwriting-recognition-matolotib-a6b31e2b166a https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python Exercise on Decision Tree: https://www.datacamp.com/community/tutorials/decision-tree-classification-python Exercise on SVM: https://stackabuse.com/implementing-sym-and-kernel-sym-with-pythons-scikit-leam/ Perform Logistics Perform Logisti	47	Dandas		2.4
Stats	47.	Pandas		3,4
https://www.w3schools.com/python/pandas correlations.asp 2	40	Danadaa		0.4
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Stats Perform Standard Deviation: https://www.w3schools.com/python/python ml mean median mode.asp 2				
Stats	49.			2
https://www.w3schools.com/python/python ml standard deviation.asp Implement Linear Regression International Reg		<u> </u>		
51. Machine Learning Implement Linear Regression https://stackabuse.com/linear-regression-in-python-with-scikit-learn/ 52. 52. Machine Learning Perform Logistics Regression: https://towardsdatascience.com/logistic-regression-using-python-skleam-numpy-mnist-handwriting-recognition-matplotilib-abb31e2b168a https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python 55. 53. Machine Learning Exercise on Decision Tree: https://www.datacamp.com/community/tutorials/decision-tree-classification-python 66. 54. Machine Learning Exercise on SVM: https://stackabuse.com/implementing-sym-and-kernel-sym-with-pythons-scikit-learn/ https://stackabuse.com/implementing-sym-and-kernel-sym-with-pythons-scikit-learn/ https://www.dataquest.io/blog/tutorial-time-series-analysis-with-pandas 67. 55. Machine Learning Exercise on SVM: https://www.dataquest.io/blog/tutorial-time-series-analysis-with-pandas 67. 56. Machine Learning Demonstration of Neural Networks: https://www.analyticsvidhya.com/blog/2020/07/neural-networks-from-scratch-in-python-and-r 7 57. Deep Learning Exercise on Feed Forward neural networks: https://builtin.com/data-science/feedforward-neural-network-intro 7 58. Deep Learning Exercise on Neural Network: https://www.analyticsvidhya.com/blog/2019/08/detailed-guide-7-loss-functions-machine-learning-python-code/ 7 <td>50.</td> <td colspan="2">, or orange</td> <td>2</td>	50.	, or orange		2
Learning https://stackabuse.com/linear-regression-in-python-with-scikit-learn/ Perform Logistics Regression: https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python-skleam-numpy-mnist-handwriting-recognition-matplotilib-a6b31e2b166a https://www.datacamp.com/community/tutorials/understanding-logistic-regression-python 53. Machine Exercise on Decision Tree: Learning https://www.datacamp.com/community/tutorials/decision-tree-classification-python 54. Machine Exercise on SVM: https://stackabuse.com/implementing-svm-and-kernel-svm-with-pythons-scikit-learn/ 55. Machine Exercise on Time Series Analysis: Learning https://www.dataquesti.o/blog/tutorial-time-series-analysis-with-pandas 56. Machine Learning https://www.analyticsvidhya.com/blog/2020/07/neural-networks-from-scratch-in-python-and-r 57. Deep Exercise on MLP: https://www.analyticsvidhya.com/blog/2020/07/neural-networks-from-scratch-in-python-and-r 58. Deep Exercise on Peed Forward neural networks: https://www.analyticsvidhya.com/blog/2020/07/neural-network-intro 59. Deep Exercise on Peed Forward neural networks: https://www.analyticsvidhya.com/blog/2019/08/detailed-guide-7-loss-functions-machine-learning-python-code/ 60. Deep Exercise on Lunguistics using Machine learning in python: https://www.analyticsvidhya.com/blog/2019/08/detailed-guide-7-loss-functions-machine-learning-python-code/ 61. Deep Text Analysis https://pubn-spot.com/category/nltk/ 62. Deep Deep Learning Peep Demonstrate Convolution Neural Network: https://bovardsdatascience.com/a-com/prehensive-guide-to-convolutional-neural-networks-s-datasets/) 63. Deep Demonstrate Convolution Neural Network: https://www.analyticsvidhya.com/blog/2020/02/learn-image-classification-cnn-convolutional-neural-networks-3-datasets/)		 		
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Annexure-II

SUGGESTIVE FORMAT AND SEQUENCE ORDER OF MOTIVATIONAL LECTURE.

Mentor

Mentors are provided an observation checklist form to evaluate and share their observational feedback on how students within each team engage and collaborate in a learning environment. The checklist is provided at two different points: Once towards the end of the course. The checklists are an opportunity for mentors to share their unique perspective on group dynamics based on various team activities, gameplay sessions, pitch preparation, and other sessions, giving insights on the nature of communication and teamwork taking place and how both learning outcomes and the student experience can be improved in the future.

Session-1 (Communication):

Please find below an overview of the activities taking place Session plan that will support your delivery and an overview of this session's activity.

Session- 1 OVERVIEW

Aims and Objectives:

- To introduce the communication skills and how it will work
- Get to know mentor and team build rapport and develop a strong sense of a team
- Provide an introduction to communication skills
- Team to collaborate on an activity sheet developing their communication, teamwork, and problem-solving
- Gain an understanding of participants' own communication skills rating at the start of the program

Activity:	Participant Time	Teacher Time	Mentor Time
Intro Attend and contribute to the scheduled.			
Understand good communication skills and how it works.			
Understand what good communication skills mean			

Understand what skills are important for good communication skills		
Key learning outcomes:	Resources:	Enterprise skills developed:
 Understand the communication skills and how it works. Understand what communication skills mean Understand what skills are important for communication skills 	 Podium Projector Computer Flip Chart Marker 	Communication Self Confidence Teamwork

Schedule	Mentor Should do
Welcome:	Short welcome and ask the Mentor to introduce
5 min	him/herself.
	Provide a brief welcome to the qualification for the class.
	Note for Instructor: Throughout this session, please monitor the session to ensure nothing inappropriate is being happened.
Icebreaker: 10 min	Start your session by delivering an icebreaker, this will enable you and your team to start to build rapport and create a team presentation for the tasks ahead. The icebreaker below should work well at introductions and encouraging communication, but feel free to use others if you think they are more appropriate. It is important to encourage young people to get to know each other and build strong team links during the first hour; this will help to increase their motivation and communication throughout the sessions.

Introduction & Onboarding: 20mins

Provide a brief introduction of the qualification to the class and play the "Onboarding Video or Presentation". In your introduction cover the following:

- 1. Explanation of the program and structure.
- 2. How you will use your communication skills in your professional life.
- 3. Key contacts and key information e.g. role of teacher, mentor, and SEED. Policies and procedures (user agreements and "contact us" section). Everyone to go to the Group Rules tab at the top of their screen, read out the rules, and ask everyone to verbally agree. Ensure that the consequences are clear for using the platform outside of hours. (9am-8pm)
- 4. What is up next for the next 2 weeks ahead so young people know what to expect (see pages 5-7 for an overview of the challenge). Allow young people to ask any questions about the session topic.

Team Activity Planning: 30 minutes

MENTOR: Explain to the whole team that you will now be planning how to collaborate for the first and second collaborative Team Activities that will take place outside of the session. There will not be another session until the next session so this step is required because communicating and making decisions outside of a session requires a different strategy that must be agreed upon so that everyone knows what they are doing for this activity and how.

- "IDENTIFY ENTREPRENEURS" TEAM ACTIVITY
- "BRAINSTORMING SOCIAL PROBLEMS" TEAM ACTIVITY"

As a team, collaborate on a creative brainstorm on social problems in your community. Vote on the areas

	you feel most passionate about as a team, then write down what change you would like to see happen. Make sure the teams have the opportunity to talk about how they want to work as a team through the activities e.g. when they want to complete the activities, how to communicate, the role of the project manager, etc. Make sure you allocate each young person a specific week that they are the project manager for the weekly activities and make a note of this. Type up notes for their strategy if this is helpful - it can be included underneath the Team Contract.
Session Close: 5 minutes	MENTOR: Close the session with the opportunity for anyone to ask any remaining questions. Instructor: Facilitate the wrap-up of the session. A quick reminder of what is coming up next and when the next session will be.

Motivational Lectures Link

Topic	Speaker	Link
How to face Problems in life	Qasim Ali Shah	https://www.youtube.com/watch?v=OrQte08MI90
1 TODICITIS III IIIC	Mr. Menk	https://www.youtube.com/watch?v=jL28c7n2Wzo&pp=y
		gUPbWVuayBtb3RpdmF0aW9u
Just control your	Qasim Ali Shah	https://www.youtube.com/watch?v=JzFs yJt-w
Emotions	Mr. Menk	https://www.youtube.com/watch?v=UDE52Cr3c3w
How to Communicate	Qasim Ali Shah	https://www.youtube.com/watch?v=PhHAQEGehKc
effectively	Mr. Menk	https://www.youtube.com/watch?v=pK5bDFAjvpc
Your attitude is	Tony Robbins	https://www.youtube.com/watch?v=5fS3rj6elFg
Everything	NA NA 1	https://www.youtube.com/watch?v=9vxH7iWS100
	Mr. Menk	https://www.youtube.com/watch?v=LJbRAK_Sp9E
Defeat fear, build	Shaykh Atif Ahmed	https://www.youtube.com/watch?v=s10dzfbozd4
Confidence	NA: NA:l.	https://www.youtube.com/watch?v=ifz4ni6Os0E
	Mr. Menk	https://www.youtube.com/watch?v=3MqN7lptaj4
Wisdom of The eagle	Learn Kurooji	https://www.youtube.com/watch?v=bEU7V5rJTtw
The power of attitude	Titan Man	https://www.youtube.com/watch?v=r8LJ5X2ejqU
How to ace your exams	Mr. Zia	https://www.youtube.com/watch?v=F4pP4O-VPn0
Hopelessness	Mr. Ali	https://www.youtube.com/watch?v=yaVEqDU8Rkg

Annexure-III

Success Story

Success story is a source of motivation for the trainees and can be presented in several ways/forms in a NAVTTC skill development course as under: -

- **1.** To call a passed out successful trainee of the institute. He will narrate his success story to the trainees in his own words and meet trainees as well.
- **2.** To see and listen to a recorded video/clip (5 to 7 minutes) showing a successful trainee Audio-video recording that has to cover the above-mentioned points.*
- **3.** The teacher displays the picture of a successful trainee (name, trade, institute, organization, job, earning, etc) and narrates his/her story in the teacher's own motivational words.
 - * The online success stories of renowned professional can also be obtained from Annex-II

Annexure-IV:

Workplace/Institute Ethics Guide

Work ethic is a standard of conduct and values for job performance. The modern definition of what constitutes good work ethics often varies. Different businesses have different expectations. Work ethic is a belief that hard work and diligence have a moral benefit and an inherent ability, virtue, or value to strengthen character and individual abilities. It is a set of values-centered on the importance of work and manifested by determination or desire to work hard.

The following ten work ethics are defined as essential for student success:

1. Attendance:

Be at work every day possible, plan your absences don't abuse leave time. Be punctual every day.

2. Character:

Honesty is the single most important factor having a direct bearing on the final success of an individual, corporation, or product. Complete assigned tasks correctly and promptly. Look to improve your skills.

3. Team Work:

The ability to get along with others including those you don't necessarily like. The ability to carry your weight and help others who are struggling. Recognize when to speak up with an idea and when to compromise by blend ideas together.

4. Appearance:

Dress for success set your best foot forward, personal hygiene, good manner, remember that the first impression of who you are can last a lifetime

5. Attitude:

Listen to suggestions and be positive, accept responsibility. If you make a mistake, admit it. Values workplace safety rules and precautions for personal and co-worker safety. Avoids unnecessary risks. Willing to learn new processes, systems, and procedures in light of changing responsibilities.

6. Productivity:

Do the work correctly, quality and timelines are prized. Get along with fellows, cooperation is the key to productivity. Help out whenever asked, do extra without being asked. Take pride in your work, do things the best you know-how. Eagerly focuses energy on accomplishing Artificial Intelligence Machine Learning

tasks, also referred to as demonstrating ownership. Takes pride in work. Deep Learning

7. Organizational Skills:

Make an effort to improve, learn ways to better yourself. Time management; utilize time and resources to get the most out of both. Take an appropriate approach to social interactions at work. Maintains focus on work responsibilities.

8. Communication:

Written communication, being able to correctly write reports and memos. Verbal communications, being able to communicate one on one or to a group.

9. Cooperation:

Follow institute rules and regulations, learn and follow expectations. Get along with fellows, cooperation is the key to productivity. Able to welcome and adapt to changing work situations and the application of new or different skills.

10.Respect:

Work hard, work to the best of your ability. Carry out orders, do what's asked the first time. Show respect, accept, and acknowledge an individual's talents and knowledge. Respects diversity in the workplace, including showing due respect for different perspectives, opinions, and suggestions.