



Master's Degree Deep Learning

» Modality: online

» Duration: 12 months

» Certificate: TECH Global University

» Credits: 60 ECTS

» Schedule: at your own pace

» Exams: online

Website: www.techtitute.com/us/information-technology/master-degree/master-deep-learning

Index

02 Objectives Introduction p. 4 p. 8 05 03 **Course Management** Skills **Structure and Content** p. 12 p. 16 p. 20 06 07 Methodology Certificate p. 30 p. 38

01 Introduction

The technological boom of recent years is especially due to the evolution of Deep Learning. Thus, at present, new challenges are assumed, applied to its improvement and its repercussion in various sectors such as the industrial, Gaming, automotive or health sectors. In all of them, technology capable of intelligently detecting failures, automating processes or creating more precise diagnostic devices is sought. In this scenario, the profile of the computer scientist with extensive technical knowledge in this field is of great importance. For this reason, TECH has designed this degree that provides the most advanced program on Artificial Intelligence and Deep Learning on the academic scene. In addition, in a 100% online format, with the most innovative educational content, prepared by consolidated specialists in the sector.



tech 06 | Introduction

The rapid technological evolution of recent years has meant that the self-driving vehicle, the early diagnosis of serious illnesses through high-precision imaging devices or facial recognition with mobile applications are not so far away. Thus, at present, these emerging innovations seek to improve the precision of automatisms and improve the quality of the results obtained.

A scenario, where the IT professional who must have exhaustive knowledge about Deep Learningplays a determining role, being also able to take another step in this race in the sector to create authentic Artificial Intelligence. For this reason, TECH has created this 12-month Master's Degree with the most advanced and current syllabus, prepared by true experts in this field.

A program with a theoretical-practical perspective that will lead students to acquire intensive learning about mathematical fundamentals, the construction of neural networks, model customization, and training with TensorFlow. A breadth of content that will be much easier to assimilate thanks to the video summaries of each topic, the videos in focus the specialized readings and the case studies. Likewise, with the Relearningsystem, used by TECH, the computer scientist will progress more naturally through this program, consolidating the new concepts more easily, thus reducing the long hours of study.

A university education that focuses on the knowledge that will make the student grow professionally, who also wants to make a first-level academic option compatible with their daily activities. And it is that all you need is a digital device with an internet connection to access this degree at the academic forefront at any time.

This **Master's Degree in Deep Learning** contains the most complete and up-to-date program on the market. The most important features include:

- The development of practical cases presented by experts in Data Engineer and Data Scientist
- The graphic, schematic and practical contents of the book provide technical and practical information on those disciplines that are essential for professional practice
- Practical exercises where self-assessment can be used to improve learning
- Its special emphasis on innovative methodologies
- Theoretical lessons, questions for the expert, debate forums on controversial topics, and individual reflection assignments
- Content that is accessible from any fixed or portable device with an Internet connection



Succeed with your AI projects in sectors such as the automotive, finance or medical sectors with the teaching provided by TECH"



Delve whenever you want into the Hugging Face transformer libraries and other natural language processing tools to apply to vision problems"

The program's teaching staff includes professionals from sector who contribute their work experience to this educational program, as well as renowned specialists from leading societies and prestigious universities.

Its multimedia content, developed with the latest educational technology, will provide the professional with situated and contextual learning, i.e., a simulated environment that will provide an immersive education designed to learn in real situations.

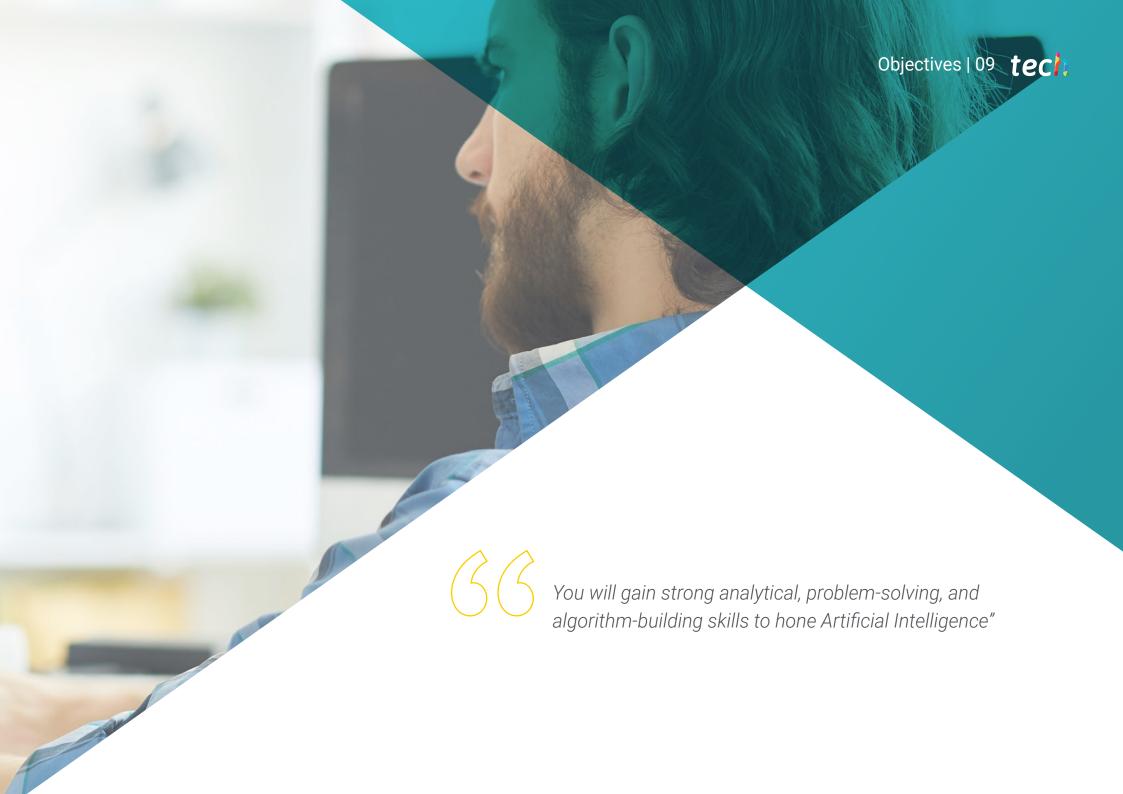
The design of this program focuses on Problem-Based Learning, by means of which the professional must try to solve different professional practice situations that are presented throughout the academic course. For this purpose, the student will be assisted by an innovative interactive video system created by renowned experts.

You have an advanced agenda in Deep Learning, 24 hours a day, from any digital device with an internet connection.

A 12-month Master's Degree with the application of deep learning techniques in real problems.







tech 10 | Objectives



General Objectives

- Fundamental key concepts of mathematical functions and their derivatives
- Apply these principles to deep learning algorithms to learn automatically
- Examine the key concepts of Supervised Learning and how they apply to neural network models
- Discuss the training, evaluation, and analysis of neural network models
- Provide a foundation for the key concepts and main applications of deep learning
- Implement and optimize neural networks with Keras
- Develop specialized knowledge about training deep neural networks
- Analyze the optimization and regularization mechanisms necessary for the training of deep networks



TECH adapts to your professional needs and motivations, which is why it has designed the most complete and flexible program on Deep Learning"



Specific Objectives

Module 1. Deep Learning Fundamentals

- Develop the chain rule to calculate derivatives of nested functions
- Analyze how new functions are created from existing functions and how their derivatives are computed
- Examine the concept of the Backward Pass and how derivatives of vector functions are applied to learn automatically
- Learn about how to use TensorFlow to build custom models
- Understand how to load and process data using TensorFlow tools
- Ground the key concepts of NLP natural language processing with RNN and attention mechanisms
- Explore the functionality of the Hugging Face transformer libraries and other natural language processing tools to apply to vision problems
- Learn to build and train models of autoencoders, GANs and diffusion models
- Understand how autoencoders can be used to efficiently encode data

Module 2. Deep Learning Principles

- Analyze the operation of linear regression and how it can be applied to neural network models
- Fundamental hyperparameter optimization to improve the performance of neural network models
- Determine how the performance of neural network models can be evaluated by using the training set and the test set

Module 3. Neural networks, the basis of Deep Learning

- Analyze the architecture of neural networks and their operating principles
- Determine how neural networks can be applied to a variety of problems
- Establish how to optimize the performance of deep learning models by tuning hyperparameters

Module 4. Training of Deep Neural Networks

- Analyze gradient problems and how they can be avoided
- Determine how to reuse pretrained layers to train deep neural networks
- Establish how to schedule the learning rate to get the best results

Module 5. Customization of Models and training with TensorFlow

- Determine how to use the TensorFlow API to define custom graphs and functions
- Fundamental use of the tf.data API to load and preprocess data efficiently
- Discuss the TensorFlow Datasets project and how it can be used to facilitate access to preprocessed datasets

Module 6. Deep Computer Vision with Convolutional Neural Networks

- Explore and understand how the convolutional and pooling layers work for the Visual Cortex architecture
- Develop CNN architectures with Keras
- Use pre-trained Keras models for object classification, location, detection and tracking, as well as semantic segmentation

Module 7. Processing sequences using RNN (Recurrent Neural Networks) and CNN (Convolutional Neural Networks)

- Analyze the architecture of neurons and recurrent layers
- Examine the various training algorithms for training RNN models
- Evaluate the performance of RNN models using accuracy and sensitivity metrics

Module 8. Natural Language Processing (NLP) with Recursive Natural Networks (RNN) and Attention

- Generate text using recurrent neural networks
- Training an encoder-decoder network to perform neural machine translation
- Develop a practical application of natural language processing with RNN and attention

Module 9. Autoencoders, GANs, and Diffusion Models

- Implement PCA techniques with an incomplete linear autoencoder
- Use convolutional and variational autoencoders to improve autoencoder results
- Analyze how GANs and diffusion models can generate new and realistic images

Module 10. Reinforcement Learning

- Using gradients to optimize an agent's policy
- Evaluate the use of neural networks to improve the accuracy of an agent when making decisions
- Implement different reinforcement algorithms to improve the performance of an agent





tech 14 | Skills

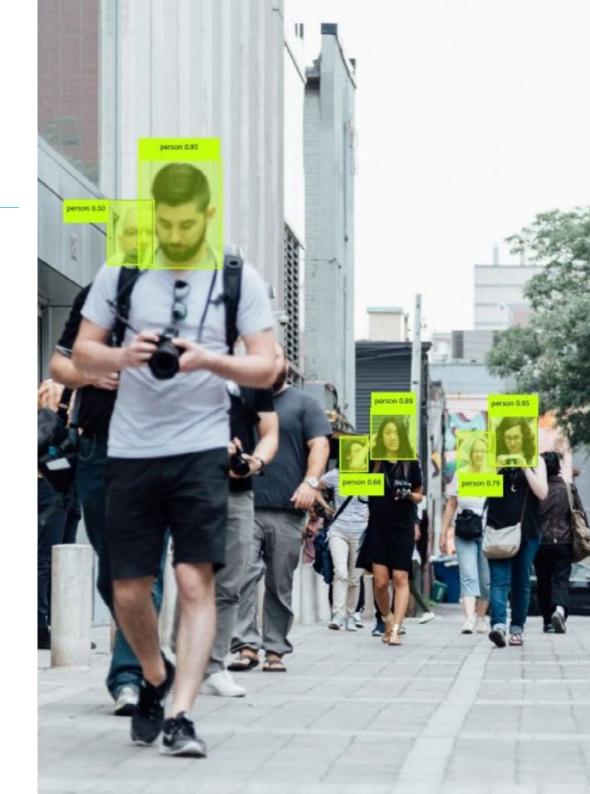


General Skills

- Implement Visual Cortex architecture
- Use pretrained Keras models for transfer learning and other computer vision tasks
- Mastering the Recurrent Neural Network (RNN)
- Train and evaluate an RNN model for time series prediction
- Improve the ability of an agent to make optimal decisions in an environment
- Increase the efficiency of an agent by learning with rewards



You will fully master the TensorFlow tool and build top-level deep learning models"







Specific Skills

- Solve problems with data, which involves improving existing processes and developing new processes through the use of appropriate technological tools
- Implement data-driven projects and tasks
- Use metrics such as precision, accuracy, and classification error
- Optimize the parameters of a neural network
- Build custom models using the TensorFlow API
- Implement with Keras tasks such as classification, localization, object detection and tracking, as well as semantic segmentation
- Generate new and realistic images
- Implement Deep Q-Learning and variants of Deep Q-Learning
- Use optimization techniques for training
- Successfully train deep neural networks



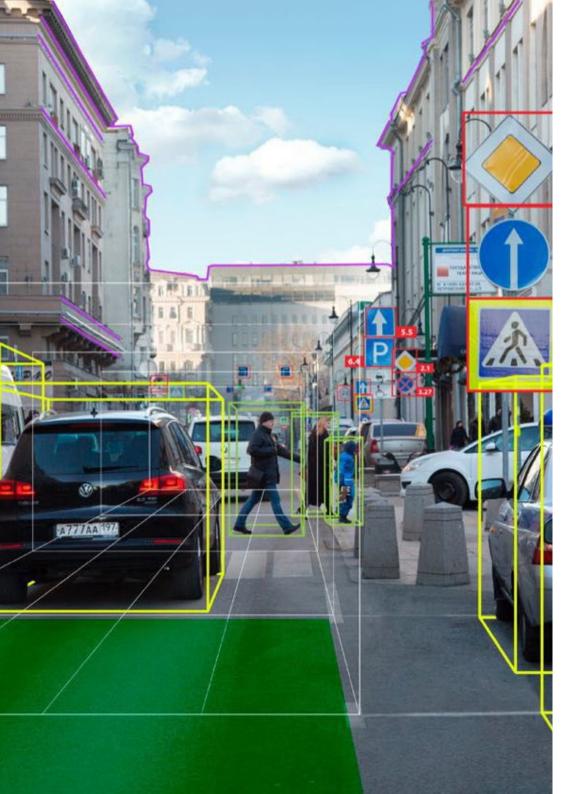


Management



Mr. Gil Contreras, Armando

- Lead Big Data Scientist-Big Data in Jhonson Controls
- Data Scientist-Big Data in Opensistemas
- Fund Auditor in Creativity and Technology and PricewaterhouseCoopers
- Lecturer at EAE Business School
- Bachelor of Economics from the Technological Institute of Santo Domingo INTEC
- Master in Data Science at the University Center for Technology and Ar
- MBA in International Relations and Business at the Center for Financial Studies CEF
- Postgraduate in Corporate Finance at the Technological Institute of Santo Domingo



Professors

Mr. Delgado Panadero, Angel

- ML Engineer at Paradigma Digital
- Computer Vision Engineer at NTT Disruption
- Data Scientist at Singular People
- Data Analytics at Parclick
- Tutor in Master in Big data and Analytics at EAE Business School
- Degree in Physics from the University of Salamanca

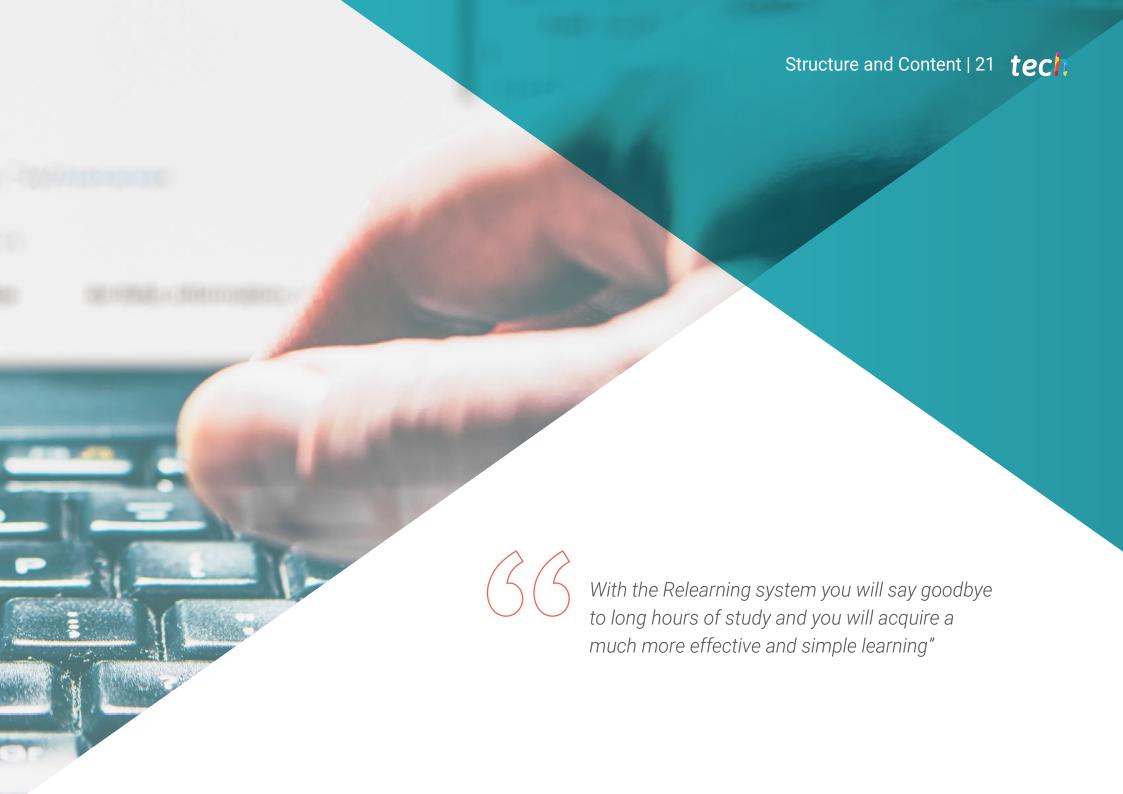
Mr. Matos, Dionis

- Data Engineer in Wide Agency Sodexo
- Data Consultant enTokiota Site
- Data Engineer in Devoteam Testa Home
- Business Intelligence Developer in Ibermatica Daimler
- Master's Degree in Big Data and Analytics /Project Management(Minor) at EAE Business School

Mr. Villar Valor, Javier

- Director and founding partner Impulsa2
- Head of Operations at Summa Insurance Brokers
- Responsible for identifying opportunities for improvement at Liberty Seguros
- Director of Transformation and Professional Excellence at Johnson Controls Iberia
- Responsible for the organization of the company Groupama Seguros
- Responsible for the Lean Six Sigma methodology at Honeywell
- Director of Quality and Purchasing at SP& PO
- Teacher at the European Business School





tech 22 | Structure and Content

Module 1. Deep Learning Fundamentals

- 1.1. Functions and Derivatives
 - 1.1.1. Linear Functions
 - 1.1.2. Partial Derivative
 - 1.1.3. Higher Order Derivatives
- 1.2. Multiple Nested Functions
 - 1.2.1. Compound Functions
 - 1.2.2. Innverse Functions
 - 1.2.3. Recessive Functions
- 1.3. Chain Rule
 - 1.3.1. Function Derivatives Nested
 - 1.3.2. Derivatives of Compound Functions
 - 1.3.3. Function Derivatives Inverse
- 1.4. Functions with Multiple Entries
 - 1.4.1. Multi-variable Functions
 - 142 Vectorial Functions
 - 1.4.3. Matrix Functions
- 1.5. Derivatives of Functions with Multiple Entries
 - 1.5.1. Partial Derivative
 - 1.5.2. Directional Derivatives
 - 1.5.3. Mixed Derivatives
- 1.6. Functions with Multiple Entries Diseases
 - 1.6.1. Vectorial Linear Functions
 - 1.6.2. Vectorial Non-Linear Functions
 - 1.6.3. Vectorial of Matrix Functions
- 1.7. Creating New Functions From Existing Functions
 - 1.7.1. Functions Sum
 - 1.7.2. Functions Product
 - 1.7.3. Functions Composition
- 1.8. Derivatives of Functions with Multiple Vectorial Entries
 - 1.8.1. Function Derivatives Lineal
 - 1.8.2. Function Derivatives Non-linear
 - 1.8.3. Derivatives of Compound Functions

- 1.9. Funciones Vectoriales and their Derivatives: Always Go One Step Further
 - 1.9.1. Directional Derivatives
 - 1.9.2. Mixed Derivatives
 - 1.9.3. Matriix Derivatives
- 1.10. Backward Pass
 - 1.10.1. Error Propagation
 - 1.10.2. Application of Update Rules
 - 1.10.3. Parameter Optimization

Module 2. Deep Learning Principles

- 2.1. Supervised Learning
 - 2.1.1. Supervised Learning Machines
 - 2.1.2. Uses of Supervised Learning
 - 2.1.3. Differences between Supervised and Unsupervised Learning
- 2.2. Supervised Learning Models
 - 2.2.1. Linear Models
 - 2.2.2. Models of Decision Trees
 - 2.2.3. Models of Neural Networks
- 2.3. Linear Regression
 - 2.3.1. Simple Linear Regression
 - 2.3.2. Multiple Linear Regression
 - 2.3.3. Regression Analysis
- 2.4. Model Training
 - 2.4.1. Batch Learning
 - 2.4.2. Online Learning
 - 2.4.3. Optimization Methods
- 2.5. Model Evaluation Training Set Versus Test Set
 - 2.5.1. Evaluation Metrics
 - 2.5.2. Cross Validation
 - 2.5.3. Comparison of Data Sets

- 2.6. Model Evaluation The Code
 - 2.6.1. Prediction Generation
 - 2.6.2. Error Analysis
 - 2.6.3. Evaluation Metrics
- 2.7. Variable Analysis
 - 2.7.1. Identification of Relevant Variables
 - 2.7.2. Correlation Analysis
 - 2.7.3. Regression Analysis
- 2.8. Explainability of Neural Network Models
 - 2.8.1. Interpretive Model
 - 2.8.2. Visualization Methods
 - 2.8.3. Evaluation Methods
- 2.9. Optimization
 - 2.9.1. Optimization Methods
 - 2.9.2. Regularization Techniques
 - 2.9.3. The Use of Graphics
- 2.10. Hyper-Parameters
 - 2.10.1. Selection of Hyper-Parameters
 - 2.10.2. Paramters Search
 - 2.10.3. Hyper-Parameters Adjustment

Module 3. Neural networks, the basis of Deep Learning

- 3.1. Deep Learning
 - 3.1.1. Types of Learning Foundations
 - 3.1.2. Applications of Deep Learning
 - 3.1.3. Hyper-Parameters Advantages and Disadvantages of Deep Learning
- 3.2. Surgery
 - 3.2.1. Summary
 - 3.2.2. Product
 - 3.2.3. Transfer

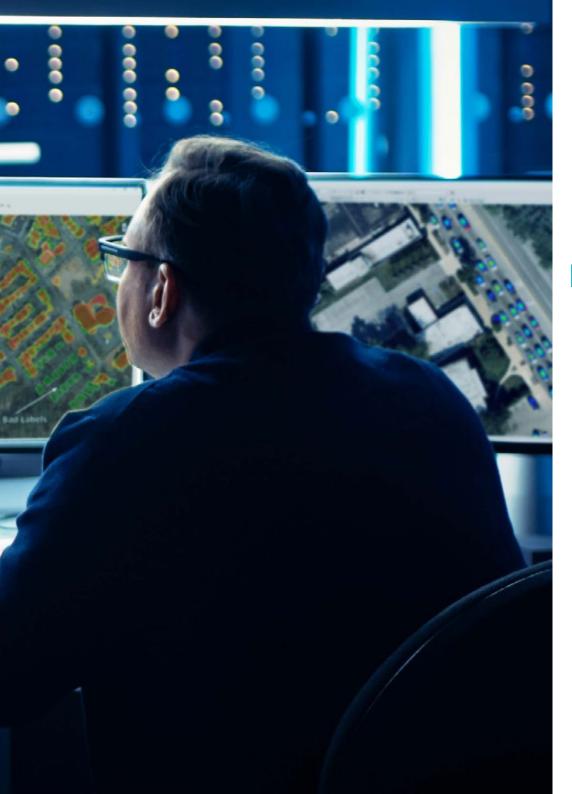
- 3.3. Layers
 - 3.3.1. Entry Layer
 - 3.3.2. Hidden Layer
 - 3.3.3. Out Layer
- 3.4. Layer Union and Operations
 - 3.4.1. Architecture Design
 - 3.4.2. Layer Connection
 - 3.4.3. Forward Propagation
- 3.5. First Neural Network Construction
 - 3.5.1. Network Design
 - 3.5.2. Weight Establishment
 - 3.5.3. Network Training
- 3.6. Trainer and Optimizer
 - 3.6.1. Optimizer Selection
 - 3.6.2. Establishment of a Loss Function
 - 3.6.3. Metric Establishment
- 3.7. Application of Neural Network Principles
 - 3.7.1. Activation Functions
 - 3.7.2. Backwards Propagation
 - 3.7.3. Parameter Adjustment
- 3.8. From Biological Neurons to Artificial Ones
 - 3.8.1. Functioning of a Biological Neuron
 - 3.8.2. Knowledge Transfer to Artificial Neurons
 - 3.8.3. Establish Relationships Between the Two
- 3.9. Implementation of MLP (Multilayer Perceptron) with Keras
 - 3.9.1. Definition of the Structure of Networks
 - 3.9.2. Model Compilation
 - 3.9.3. Model Training
- 3.10. Hyperparameters of Fine tuning of Neural Networks
 - 3.10.1. Selection of Activation Function
 - 3.10.2. Establishing relearning rate
 - 3.10.3. Weight Adjustment

tech 24 | Structure and Content

Module 4. Training of Deep Neural Networks

- 4.1. Gradient Problems
 - 4.1.1. Gradient Optimization Techniques
 - 4.1.2. Stochastic Gradients
 - 4.1.3. Weight Initialization Techniques
- 4.2. Reuse of Pretrained Layers
 - 4.2.1. Transfer of Learning Training
 - 4.2.2. Feature Extraction
 - 4.2.3. Deep Learning
- 4.3. Optimizers
 - 4.3.1. Stochastic Gradient Descent Optimizers
 - 4.3.2. Adam and RMSprop Optimizers
 - 4.3.3. Moment Optimizers
- 4.4. Learning Rate Programming
 - 4.4.1. Control of Machine Learning Rate
 - 4.4.2. Learning Cycles
 - 4.4.3. Softening Terms
- 4.5. Overfitting
 - 4.5.1. Cross Validation
 - 4.5.2. Regularization
 - 4.5.3. Evaluation Metrics
- 4.6. Guideline Practices
 - 4.6.1. Model Design
 - 4.6.2. Material Selection and Evaluation Paramters
 - 4.6.3. Hypothesis Testing
- 4.7. Transfer Learning
 - 4.7.1. Transfer of Learning Training
 - 4.7.2. Feature Extraction
 - 4.7.3. Deep Learning
- 4.8. Data Augmentation
 - 4.8.1. Image Transformation
 - 4.8.2. Generating Synthethic Data
 - 4.8.3. Text Transformation





Structure and Content | 25 tech

- 4.9. Practical Application of Transfer Learning
 - 4.9.1. Transfer of Learning Training
 - 4.9.2. Feature Extraction
 - 4.9.3. Deep Learning
- 4.10. Regularization
 - 4.10.1. L1 and L2
 - 4.10.2. Regularization by Maximum Entropy
 - 4.10.3. Dropout

Module 5. Customization of Models and training with TensorFlow

- 5.1. TensorFlow
 - 5.1.1. Use of TensorFlow Library
 - 5.1.2. TensorFlow Training Models
 - 5.1.3. TensorFlow Graphic Operations
- 5.2. TensorFlow and NumPy
 - 5.2.1. NumPy Computer Environment for TensorFlow
 - 5.2.2. Use of NumPy Arrays with TensorFlow
 - 5.2.3. NumPy Operations for TensorFlow Graphics
- 5.3. Customization of Training Models and Algorithms
 - 5.3.1. Construction of Personalized TensorFlow Models
 - 5.3.2. Management of Training Parameters
 - 5.3.3. Use Optimization Techniques for Training
- 5.4. TensorFlow Functions and Graphics
 - 5.4.1. TensorFlow Functions
 - 5.4.2. Use Graph for Model Training
 - 5.4.3. Optimization of Graphics with TensorFlow Operations
- 5.5. Load and Processing with TensorFlow Data
 - 5.5.1. Load Groups with TensorFlow Data
 - 5.5.2. Processing with TensorFlow Data
 - 5.5.3. Using TensorFlow Tools for Data Manipulations

tech 26 | Structure and Content

- 5.6. API tf.data
 - 5.6.1. Using the tf.data API for Data Processing
 - 5.6.2. Building Data Streams with tf.data
 - 5.6.3. Using the Keras Preprocessing API for Model raining
- 5.7. TFRecord Format
 - 5.7.1. Using the tf.data API for Data Processing
 - 5.7.2. Loading TFRecord Files with TensorFlow
 - 5.7.3. Using TFRecord files for Model Training
- 5.8. Keras Preprocessing Layers
 - 5.8.1. Using the Keras Preprocessing API
 - 5.8.2. Building Preprocessing Pipeline with Keras
 - 5.8.3. Using the Keras Preprocessing API for Model raining
- 5.9. TensorFlow Datasets Project
 - 5.9.1. Using TensorFlow Datasets for Data Loading
 - 5.9.2. Processing with TensorFlow Data Datasets
 - 5.9.3. Using TensorFlow Datasets for model training
- 5.10. Building a Deep Learning Application with TensorFlow. Practical Application
 - 5.10.1. Building a Deep Learning Application with TensorFlow
 - 5.10.2. TensorFlow Training Models
 - 5.10.3. Use of the Application for the Prediction of Results

Module 6. Deep Computer Vision with Convolutional Neural Networks

- 6.1. Visual Cortex Architecture
 - 6.1.1. Functions of the Visual Cortex
 - 6.1.2. Computational Vision Theory
 - 6.1.3. Image Processing Models
- 6.2. Convolution Layers
 - 6.2.1. Reuse of Weights in Convolution
 - 6.2.2. Convolution2D
 - 6.2.3. Activation Functions

- 6.3. Pooling Layers and Implementing Pooling Layers with Keras
 - 6.3.1. Pooling y Striding
 - 6.3.2. Flattening
 - 6.3.3. Types of Pooling
- 6.4. CNN Architecture
 - 6.4.1. VGG Architecture
 - 6.4.2. AlexNet Architecture
 - 6.4.3. ResNet Architecture
- 6.5. Implementation of a ResNet-34 CNN using Keras
 - 6.5.1. Weight Initialization
 - 6.5.2. Input Layer Definition
 - 6.5.3. Definition of the Exits
- 6.6. Using Pretrained Keras Models
 - 6.6.1. Characteristics of Pretrained Models
 - 6.6.2. Uses of Pretrained Models
 - 6.6.3. Advantages of Pretrained Models
- 5.7. Pretrained Models for Transfer Learning
 - 6.7.1. Transfer Learning
 - 6.7.2. Transfer Learning Process
 - 6.7.3. Transfer Learning Process
- 6.8. Classification and Location in Deep Computer Vision
 - 6.8.1. Image Classification
 - 6.8.2. Locating Objects in Images
 - 6.8.3. Object Detection
- 6.9. Object Detection of Objects and Tracking
 - 5.9.1. Objects Detection Methods
 - 5.9.2. Object Tracking algorithms
 - 5.9.3. Tracing and Localization Techniques
- 6.10. Semantic Segmentation
 - 6.10.1. Deep Learning for Semantic Segmentation
 - 6.10.2. Edge Detection
 - 6.10.3. Rule-based Segmentation Methods

Module 7. Processing sequences using RNN (Recurrent Neural Networks) and CNN (Convolutional Neural Networks)

- 7.1. Recurrent Neurons and Layers
 - 7.1.1. Types of Recurring Neurons
 - 7.1.2. Architecture of a Recurring Layer
 - 7.1.3. Applications of Recurring Layers
- 7.2. Training of Recurrent Neural Network (RNN)
 - 7.2.1. Backpropagation Through Time (BPTT)
 - 7.2.2. Stochastic Gradient Descending
 - 7.2.3. Regularization in RNN Training
- 7.3. Evaluation of RNN Models
 - 7.3.1. Evaluation Metrics
 - 7.3.2. Cross Validation
 - 7.3.3. Hyper-Parameters Adjjustment
- 7.4. RNN Pretrained
 - 7.4.1. Pretrained Network
 - 7.4.2. Learning Transfer
 - 7.4.3. Fine Tuning
- 7.5. Prognosis of a Time Series
 - 7.5.1. Statistical Models for Forecasts
 - 7.5.2. Methods of Time Series
 - 7.5.3. Neural Network-Based Models
- 7.6. Interpretation of the Results of Time Series Analysis
 - 7.6.1. Main Component Analysis
 - 7.6.2. Cluster Analysis
 - 7.6.3. Correlation Analysis
- 7.7. Handling of Long Sequences
 - 7.7.1. Long Short-Term Memory (LSTM)
 - 7.7.2. Gated Recurrent Units (GRU)
 - 7.7.3. 1D Convolutionals

- 7.8. Partial Sequence Learning
 - 7.8.1. Methods of Deep Learning
 - 7.8.2. Generic Models
 - 7.8.3. Reinforcement Learning
- 7.9. Practical Application of RNN and CNN
 - 7.9.1. Natural Language Processing
 - 7.9.2. Pattern Recognition
 - 7.9.3. Computer Vision
- 7.10. Differences in Classical Results
 - 7.10.1. Classic Methods vs. RNN
 - 7.10.2. Classic Methods vs. CNN
 - 7.10.3. Difference in Training Time

Module 8. Natural Language Processing (NLP) with Recursive Natural Networks (RNN) and Attention

- 8.1. Text Generation Using RNN
 - 8.1.1. Training an RNN for Text Generation
 - 8.1.2. Natural Language Generation with RNN
 - 8.1.3. Text Generation Applications with RNN
- 8.2. Creating the Training Data Set
 - 8.2.1. Data Preparation for Training an RNN
 - 8.2.2. Storage the Training Data Set
 - 8.2.3. Cleaning and Transformation of Date of Cultural Interest
- 8.3. Sentiment Analysis
 - 8.3.1. RNN Opinions Classification
 - 8.3.2. Detection of Topics in Comments
 - 8.3.3. Sentiment Analysis with Deep Learning Algorithms
- 8.4. Training an Encoder-decoder Network for Neural Machine Translation
 - 8.4.1. Training an RNN for Machine Translation
 - 8.4.2. Using an encoder-decoder Network for Machine Translation
 - 8.4.3. Improved Machine Translation Accuracy with RNN

tech 28 | Structure and Content

- 8.5. Attention Mechanism
 - 8.5.1. Application of Care Mechanisms in RNN
 - 8.5.2. Using Attention Mechanisms to Improve Model Accuracy
 - 8.5.3. Advantages of Attention Mechanisms in Neural Networks
- 8.6. Transformers Models
 - 8.6.1. Transformers Use Model for Natural Language Processing
 - 8.6.2. Transformers Application Model for Vision
 - 8.6.3. Advantages of Transformers Models
- 8.7. Transformers for Vision
 - 8.7.1. Transformers Use Model for Vision
 - 8.7.2. Data Pre-Processing Imaging
 - 8.7.3. Transformer Training Model for Vision
- 8.8. Hugging Face Transformers Libraries
 - 8.8.1. Use of Hugging Face Transformers Libraries
 - 8.8.2. Application of Hugging Face Transformers Libraries
 - 8.8.3. Advantage of Hugging Face Transformers Libraries
- 8.9. Other Transformers. Libraries Comparison
 - 8.9.1. Comparison between Different BookstoresTransformers
 - 8.9.2. Use of other bookstoresTransformers
 - 8.9.3. Advantages of other bookstoresTransformers
- 8.10. Develop from an Application of NLP Processing with RNN and Attention. Practical Application
 - 8.10.1. Develop from an Application of Natural Language Processing with RNN and Attention
 - 8.10.2. Use of RNN, Service Mechanisms and Transformers Models in the Application
 - 8.10.3. Evaluation of the Practical Application

Module 9. Autoencoders, GANs, and Diffusion Models

- 9.1. Representation of Efficient Data
 - 9.1.1. Dimensionality Reduction
 - 9.1.2. Deep Learning
 - 9.1.3. Compact Representation
- 9.2. Implement PCA techniques with an Incomplete Linear Autoencoder
 - 9.2.1. Training Process
 - 9.2.2. Python Implementation
 - 9.2.3. Test Data Use
- 9.3. Stacked Auto Encoders
 - 9.3.1. Deep Neural Networks
 - 9.3.2. Construction of Coding Architectures
 - 9.3.3. Use of Regularization
- 9.4. Convolutional Autoencoders
 - 9.4.1. Convolutional Model Design
 - 9.4.2. Convolutional Design Training
 - 9.4.3. Results Evaluation
- 9.5. Denoising Auto Encoders
 - 9.5.1. Filter Application
 - 9.5.2. Coding Model Design
 - 9.5.3. Use of Regularization Techniques
- 9.6. Dispersed Auto Encoders
 - 9.6.1. Increase Coding Efficiency
 - 9.6.2. Minimizing the Number of Parameters
 - 9.6.3. Use of Regularization Techniques
- 9.7. Variational Auto Encoders
 - 9.7.1. Using Variational Optimization
 - 9.7.2. Unsupervised Deep Learning
 - 9.7.3. Deep Latent Representations
- 9.8. MNIST Image Generation of Fashion
 - 9.8.1. Pattern Recognition
 - 9.8.2. Generation of Images
 - 9.8.3. Training of Deep Neural Networks

- 9.9. Generative Adversarial Networks and Diffusion Models
 - 9.9.1. Generation of Content from Images
 - 9.9.2. Models of Data Distribution
 - 9.9.3. Use of Adversarial Networks
- 9.10. Implementation of the Models. Practical Application
 - 9.10.1. Implementation of the Models
 - 9.10.2. Using Real Data
 - 9.10.3. Results Evaluation

Module 10. Reinforcement Learning

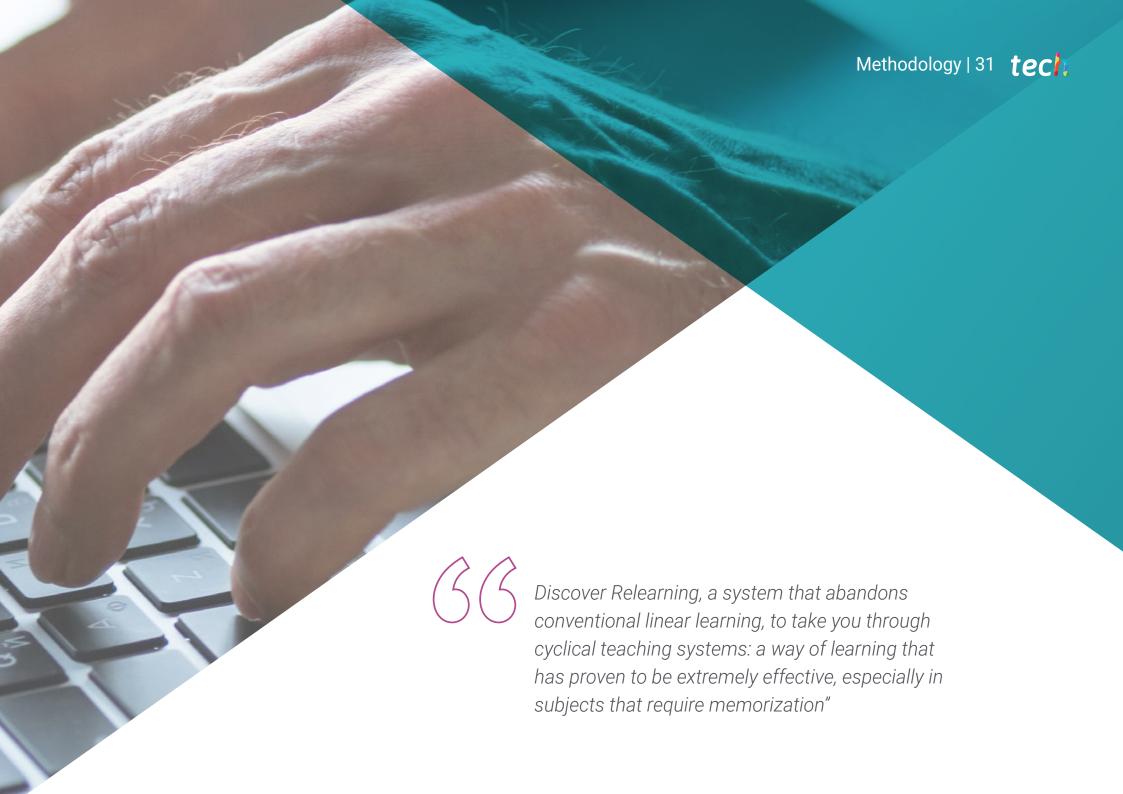
- 10.1. Policy Search and Rewards Optimization
 - 10.1.1. Reward Optimization Algorithms
 - 10.1.2. Policy Search Processes
 - 10.1.3. Reinforcement Learning to Optimize Rewards
- 10.2. OpenAl
 - 10.2.1. OpenAl Gym Environment
 - 10.2.2. Creation of OpenAI Environments
 - 10.2.3. Reinforcement Learning Algorithms
- 10.3. Politics of Neural Networks
 - 10.3.1. Convolutional Neural Networks for Policy Search
 - 10.3.2. Politics of Deep Learning
 - 10.3.3. Extension of Neural Network Policies
- 10.4. Evaluation of Actions: the Problem of the Allocation of Credits
 - 10.4.1. Risk Analysis for Credit Allocation
 - 10.4.2. Loan Profitability Estimation
 - 10.4.3. Credit Evaluation Models Based on Neural Networks
- 10.5. Policy Gradients
 - 10.5.1. Reinforcement Learning with Policy Gradients
 - 10.5.2. Policy Gradient Optimization
 - 10.5.3. Policy Gradient Algorithms
- 10.6. Markov Decision Process
 - 10.6.1. Markov Decision Process Optimization
 - 10.6.2. Reinforcement Learning for Markov Decision Processes
 - 10.6.3. Markov Decision Process Models

- 10.7. Learning and Time Differences and Q-Learning
 - 10.7.1. Using differences in Learning
 - 10.7.2. Using Q-Learning in Learning
 - 10.7.3. Optimization of Q-Learning Parameters
- 10.8. Implement from Deep Q-Learning and variants of Deep Q-Learning
 - 10.8.1. Building of Deep Neural Networks for Deep Q-Learning
 - 10.8.2. Deep Q- Learning Implementation
 - 10.8.3. Deep Q- Learning Variations
- 10.9. Reinforment Learning Algorithms
 - 10.9.1. Reinforcement Learning Algorithms
 - 10.9.2. Reward. Learning Algorithms
 - 10.9.3. Punishment Learning Algorithms
- 10.10. Reinforcement Learning an Environment Design. Practical Application
 - 10.10.1. Reinforcement Learning an Environment Design
 - 10.10.2. Reinforcement Learning an Algorithm Implementation
 - 10.10. 3 Reinforcement Learning an Algorithm Assessment



Specialize in the training, evaluation, and analysis of neural network models thanks to this Master's Degree"





tech 32 | Methodology

Case Study to contextualize all content

Our program offers a revolutionary approach to developing skills and knowledge. Our goal is to strengthen skills in a changing, competitive, and highly demanding environment.



At TECH, you will experience a learning methodology that is shaking the foundations of traditional universities around the world"



You will have access to a learning system based on repetition, with natural and progressive teaching throughout the entire syllabus.



The student will learn to solve complex situations in real business environments through collaborative activities and real cases.

A learning method that is different and innovative

This TECH program is an intensive educational program, created from scratch, which presents the most demanding challenges and decisions in this field, both nationally and internationally. This methodology promotes personal and professional growth, representing a significant step towards success. The case method, a technique that lays the foundation for this content, ensures that the most current economic, social and professional reality is taken into account.



Our program prepares you to face new challenges in uncertain environments and achieve success in your career"

The case method is the most widely used learning system in the best faculties in the world. The case method was developed in 1912 so that law students would not only learn the law based on theoretical content. It consisted of presenting students with real-life, complex situations for them to make informed decisions and value judgments on how to resolve them. In 1924, Harvard adopted

it as a standard teaching method.

What should a professional do in a given situation? This is the question we face in the case method, an action-oriented learning method. Throughout the program, the studies will be presented with multiple real cases. They will have to combine all their knowledge and research, and argue and defend their ideas and decisions.

Relearning Methodology

TECH effectively combines the Case Study methodology with a 100% online learning system based on repetition, which combines 8 different teaching elements in each lesson.

We enhance the Case Study with the best 100% online teaching method: Relearning.

In 2019, we obtained the best learning results of all online universities in the world.

At TECH you will learn using a cutting-edge methodology designed to train the executives of the future. This method, at the forefront of international teaching, is called Relearning.

Our university is the only one in the world authorized to employ this successful method. In 2019, we managed to improve our students' overall satisfaction levels (teaching quality, quality of materials, course structure, objectives...) based on the best online university indicators.



Methodology | 35 tech

In our program, learning is not a linear process, but rather a spiral (learn, unlearn, forget, and re-learn). Therefore, we combine each of these elements concentrically. With this methodology we have trained more than 650,000 university graduates with unprecedented success in fields as diverse as biochemistry, genetics, surgery, international law, management skills, sports science, philosophy, law, engineering, journalism, history, markets, and financial instruments. All this in a highly demanding environment, where the students have a strong socio-economic profile and an average age of 43.5 years.

Relearning will allow you to learn with less effort and better performance, involving you more in your training, developing a critical mindset, defending arguments, and contrasting opinions: a direct equation for success.

From the latest scientific evidence in the field of neuroscience, not only do we know how to organize information, ideas, images and memories, but we know that the place and context where we have learned something is fundamental for us to be able to remember it and store it in the hippocampus, to retain it in our long-term memory.

In this way, and in what is called neurocognitive context-dependent e-learning, the different elements in our program are connected to the context where the individual carries out their professional activity.

This program offers the best educational material, prepared with professionals in mind:



Study Material

All teaching material is produced by the specialists who teach the course, specifically for the course, so that the teaching content is highly specific and precise.

These contents are then applied to the audiovisual format, to create the TECH online working method All this, with the latest techniques that offer high quality pieces in each and every one of the materials that are made available to the student.



Classes

There is scientific evidence suggesting that observing third-party experts can be useful.

Learning from an Expert strengthens knowledge and memory, and generates confidence in future difficult decisions.



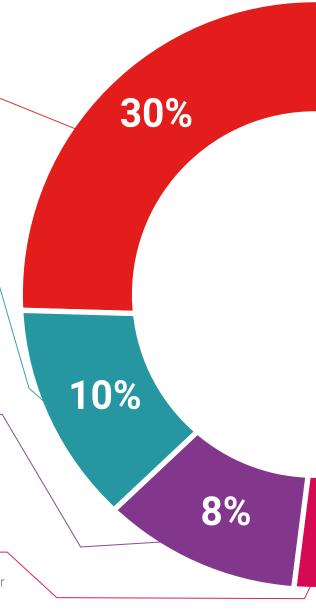
Practising Skills and Abilities

They will carry out activities to develop specific competencies and skills in each thematic area. Exercises and activities to acquire and develop the skills and abilities that a specialist needs to develop in the context of the globalization that we are experiencing.



Additional Reading

Recent articles, consensus documents and international guidelines, among others. In TECH's virtual library, students will have access to everything they need to complete their course.



Case Studies

Students will complete a selection of the best case studies chosen specifically for this program. Cases that are presented, analyzed, and supervised by the best specialists in the world.



Interactive Summaries

The TECH team presents the contents attractively and dynamically in multimedia lessons that include audio, videos, images, diagrams, and concept maps in order to reinforce knowledge.

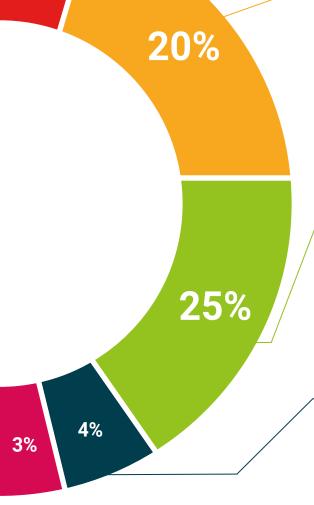


This exclusive educational system for presenting multimedia content was awarded by Microsoft as a "European Success Story".

Testing & Retesting



We periodically evaluate and re-evaluate students' knowledge throughout the program, through assessment and self-assessment activities and exercises, so that they can see how they are achieving their goals.







tech 40 | Certificate

This program will allow you to obtain your **Master's Degree diploma in Deep Learning** endorsed by **TECH Global University**, the world's largest online university.

TECH Global University is an official European University publicly recognized by the Government of Andorra (*official bulletin*). Andorra is part of the European Higher Education Area (EHEA) since 2003. The EHEA is an initiative promoted by the European Union that aims to organize the international training framework and harmonize the higher education systems of the member countries of this space. The project promotes common values, the implementation of collaborative tools and strengthening its quality assurance mechanisms to enhance collaboration and mobility among students, researchers and academics.

This **TECH Global University** title is a European program of continuing education and professional updating that guarantees the acquisition of competencies in its area of knowledge, providing a high curricular value to the student who completes the program.

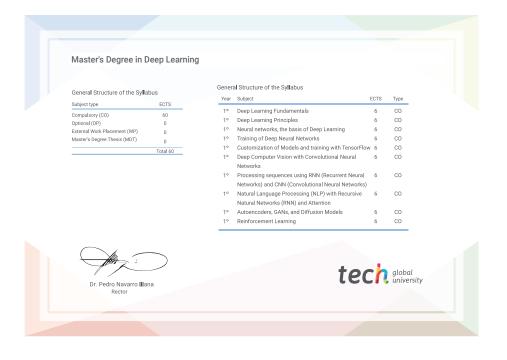
Title: Master's Degree in Deep Learning

Modality: online

Duration: 12 months

Accreditation: 60 ECTS





^{*}Apostille Convention. In the event that the student wishes to have their paper diploma issued with an apostille, TECH Global University will make the necessary arrangements to obtain it, at an additional cost.

health confidence people

education information tutors
guarantee accreditation teaching
institutions technology learning



Master's Degree Deep Learning

- » Modality: online
- » Duration: 12 months
- » Certificate: TECH Global University
- » Credits: 60 ECTS
- » Schedule: at your own pace
- » Exams: online

