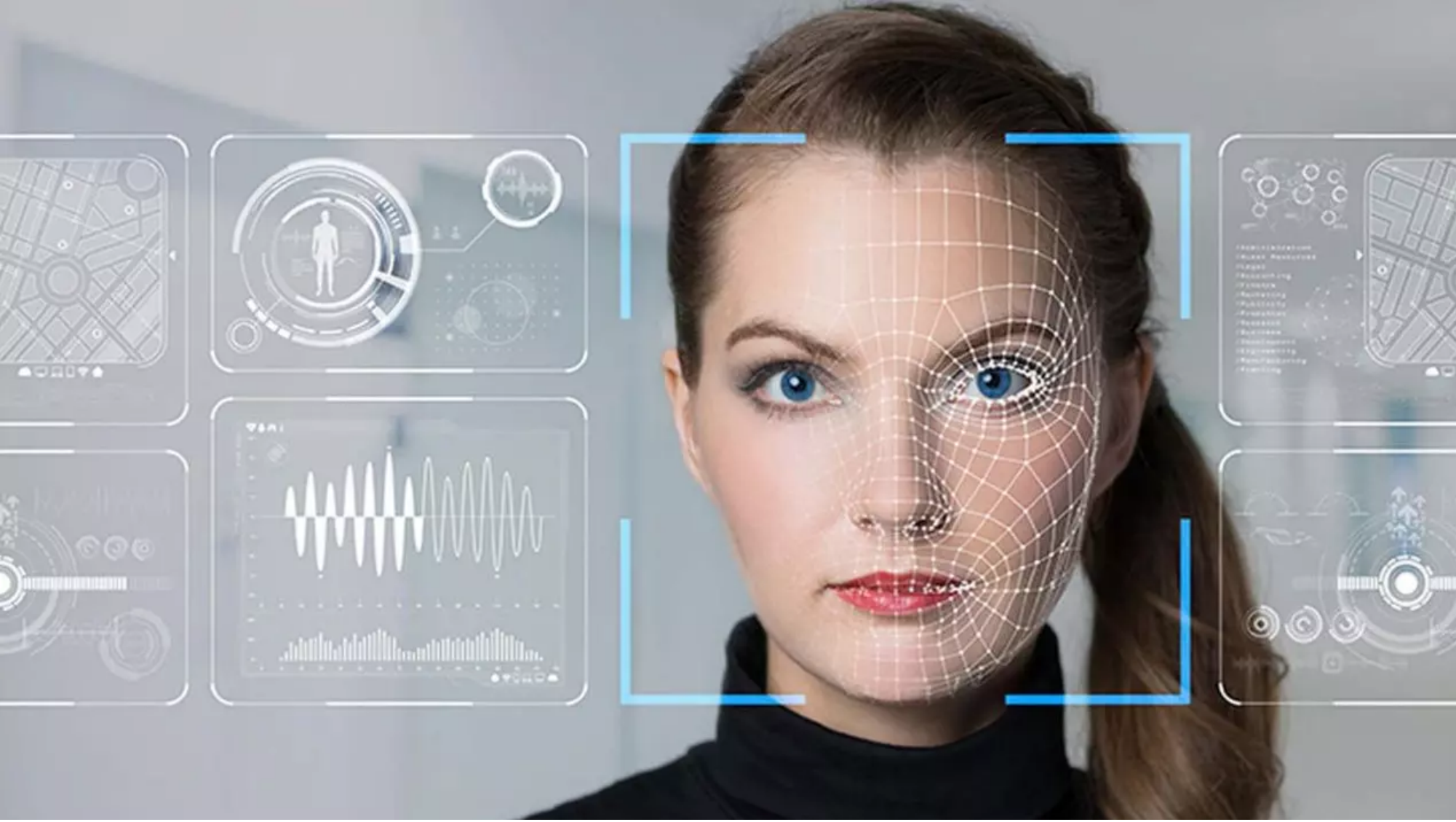


Deepfake

Outline

Definizioni

Deefake e Intelligenza Artificiale - definizioni

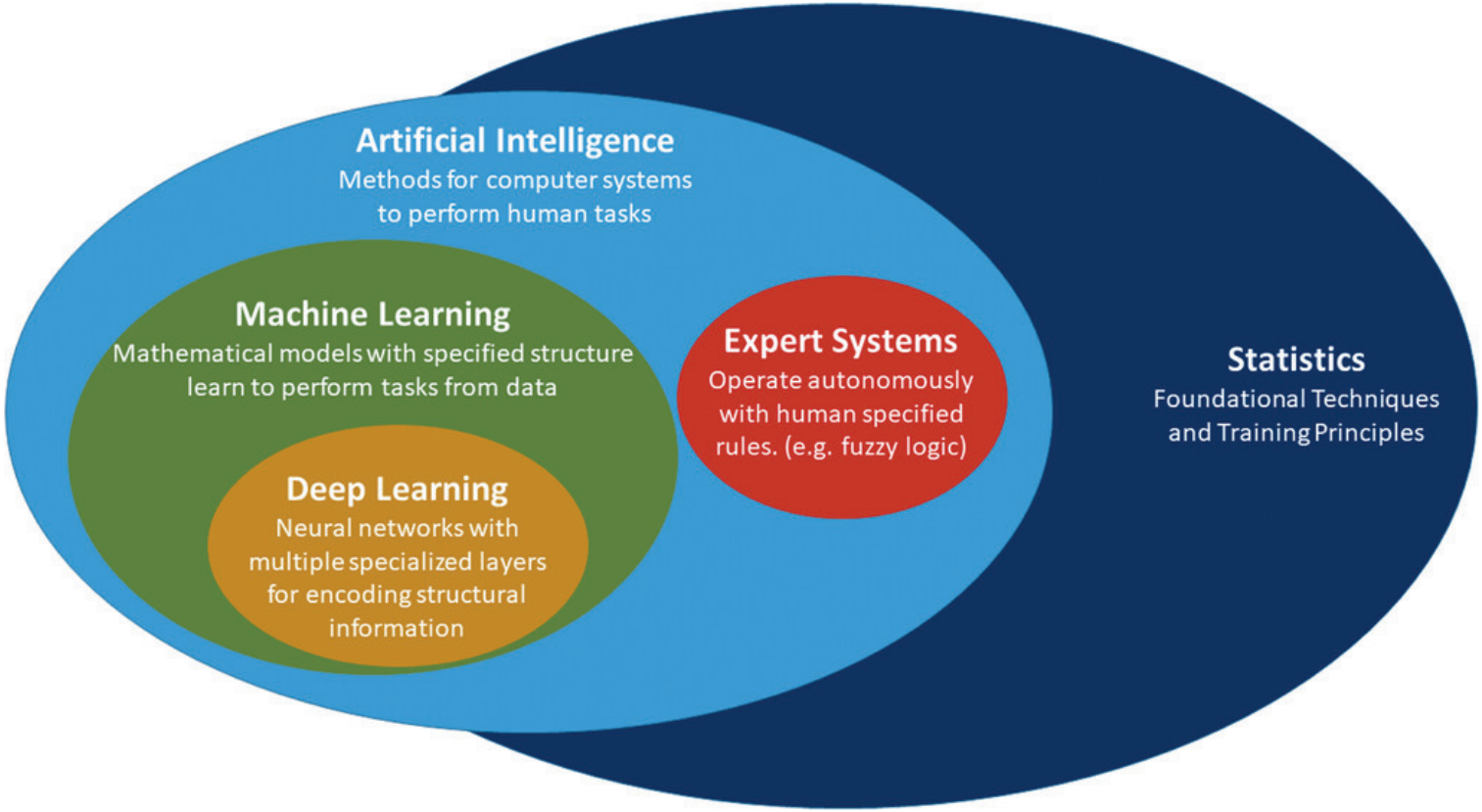
Deepfake (NSA) [1]

Contenuto multimediale creato sinteticamente o manipolato utilizzando una qualche forma di tecnologia meccanica o di deep learning.

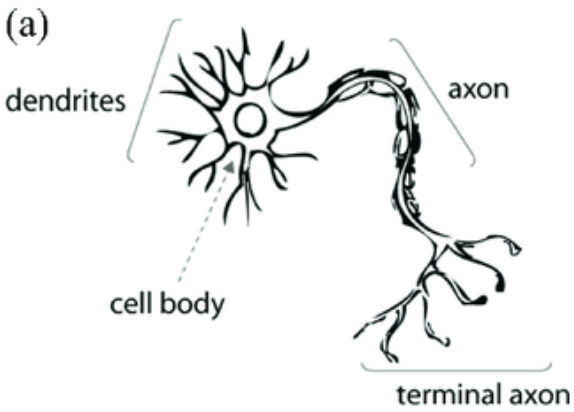
Intelligenza artificiale (NIST) [2]

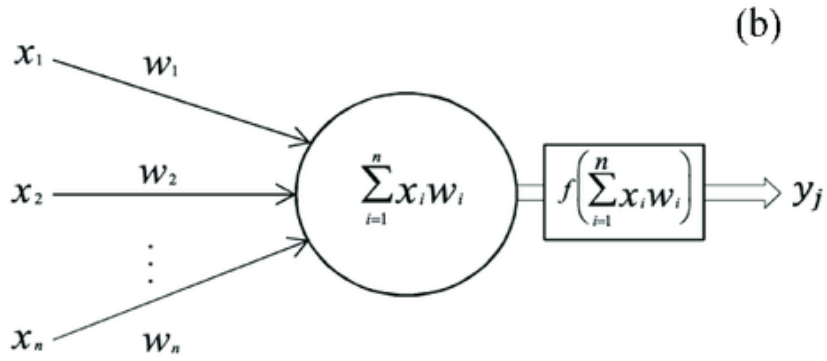
Una branca dell'informatica dedicata allo sviluppo di sistemi di elaborazione dati che svolgono funzioni normalmente associate all'intelligenza umana, come il ragionamento, l'apprendimento e l'auto-miglioramento

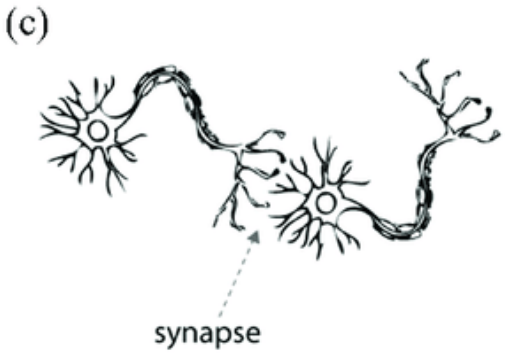
Deepfake e Intelligenza Artificiale - tassonomia [3]

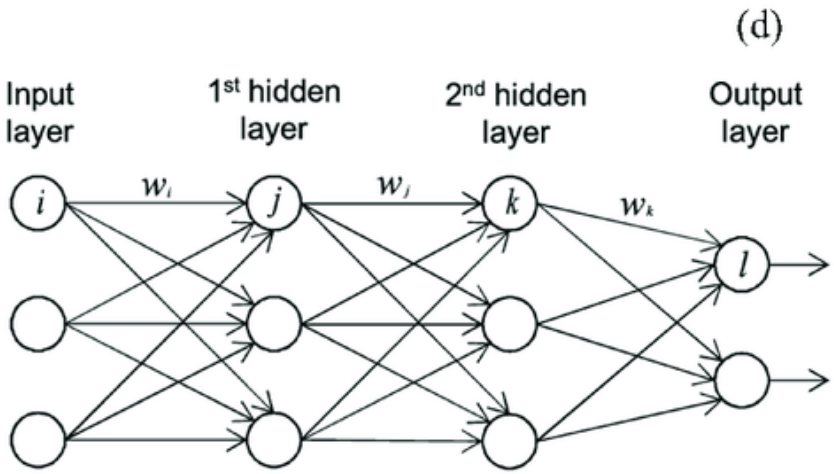


Deepfake e Intelligenza Artificiale - reti neurali [4]



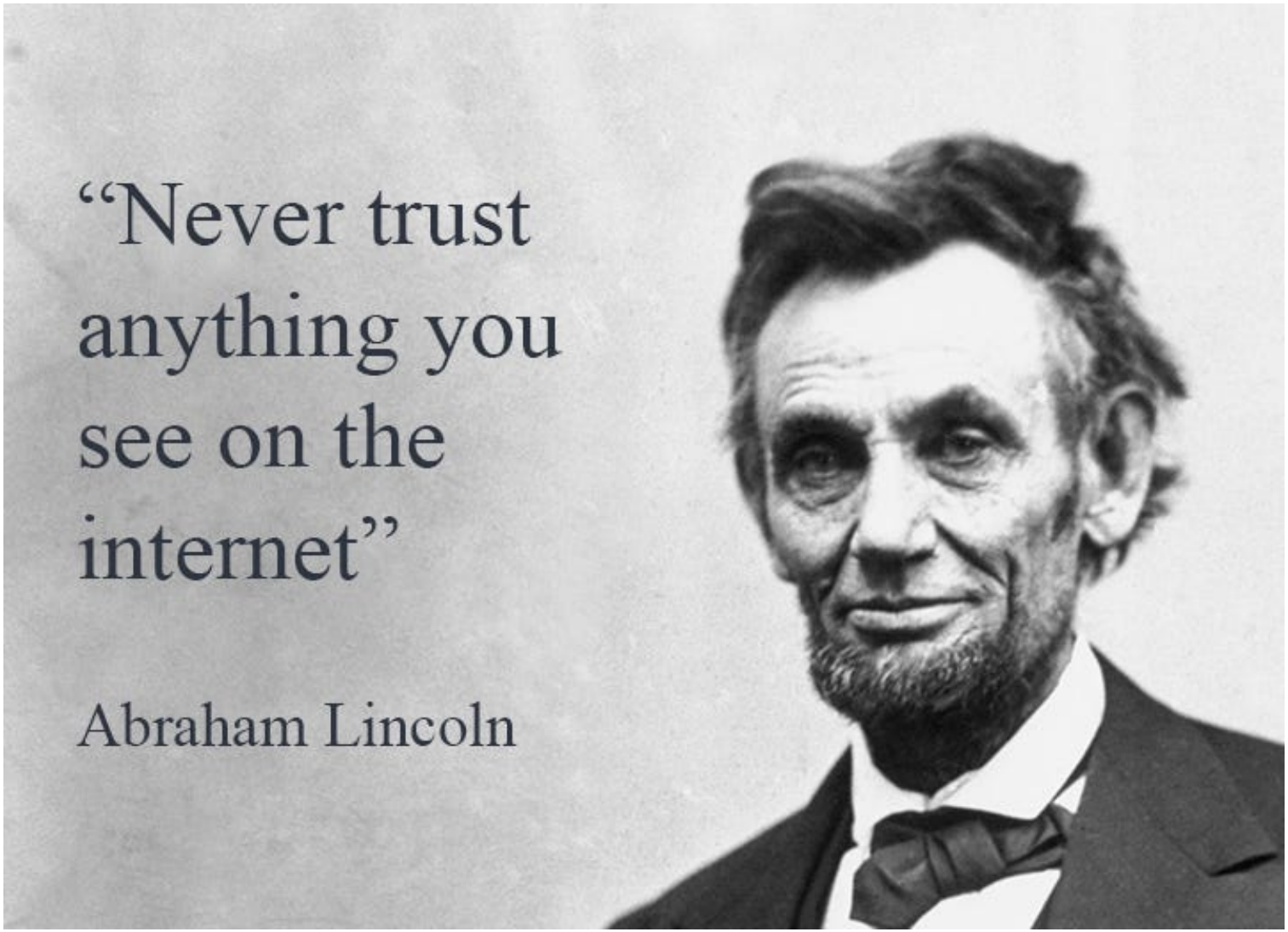






Breve storia

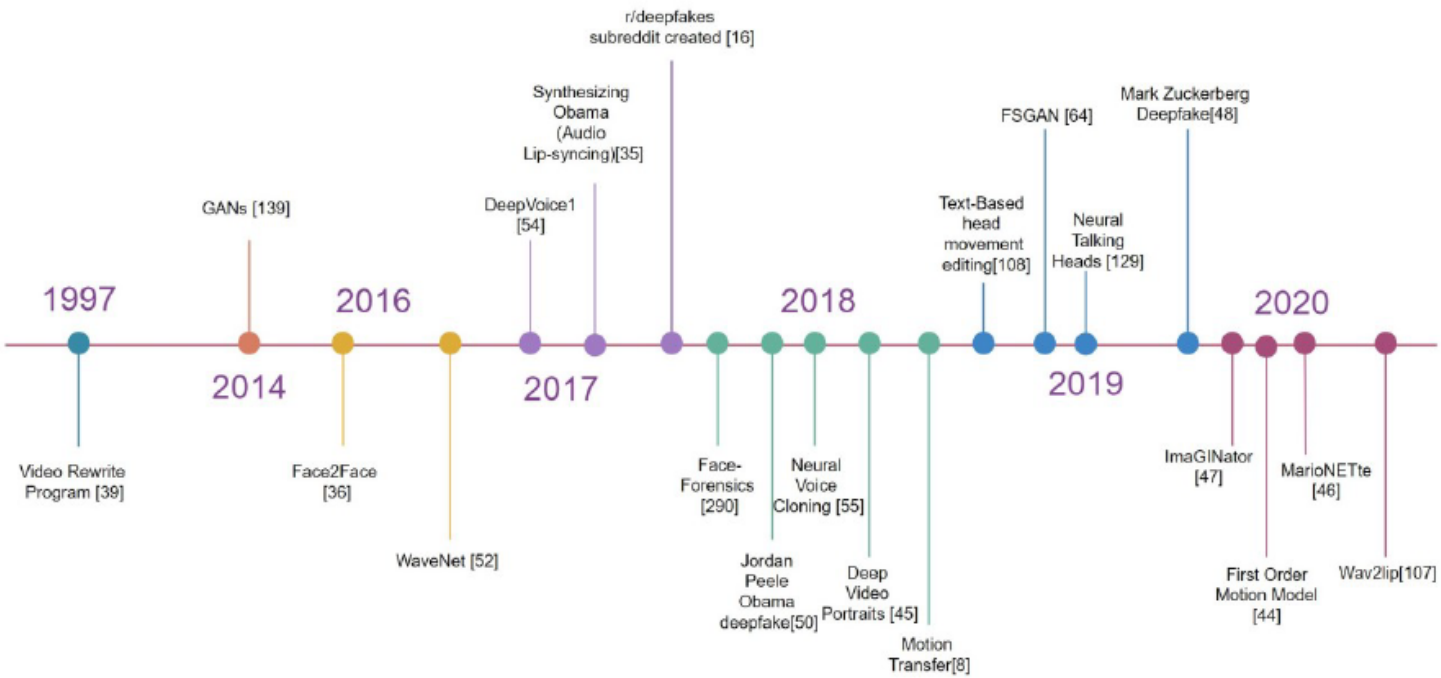
Storia dei deepfake



Storia dei deepfake: 1860 Calhoun/Lincon [5]

Storia dei deepfake: 1997 Video Rewrite (GAN) [6]

Deepfake e Intelligenza Artificiale - tassonomia [13]



Storia dei deepfake: 2017 B.Obama [7]

Print subscriptions | Sign in | Search jobs | Search | Europe edition

Support the Guardian
Fund independent journalism with €10 per month
Support us →

The Guardian

News | Opinion | Sport | Culture | Lifestyle | More

Technology

This article is more than **6 years old**

The future of fake news: don't believe everything you read, see or hear

A new breed of video and audio manipulation tools allow for the creation of realistic looking news footage, like the now infamous fake Obama speech

Olivia Solon *in San Francisco*

Wed 26 Jul 2017 07.00 CEST

Share

The University of Washington's Synthesizing Obama project took audio from one of Obama's speeches and used it to animate his face in an entirely different video

Storia dei deepfake: 2017 Imitazione della voce [8]

WSJ PRO

Fraudsters Used AI to Mimic CEO's Voice in Unusual Cybercrime Case

Scams using artificial intelligence are a new challenge for companies

By Catherine Stupp

Updated Aug. 30, 2019 12:52 pm ET | WSJ PRO

PHOTO: SIMON DAWSON/BLOOMBERG NEWS

Criminals used artificial intelligence-based software to impersonate a chief executive's voice and demand a fraudulent transfer of €220,000 ($243,000) in March in what cybercrime experts described as an unusual case of artificial intelligence being used in hacking.

The CEO of a U.K.-based energy firm thought he was speaking on the phone with his boss, the chief executive of the firm's German parent company, who asked him

MUST READS FROM CYBERSECURITY

1. Port of Rotterdam Tests Quantum Network to Defend Against Hacks

2. Okta Hack Update

Storia dei deepfake: 2020 N.Pelosi [8]

REUTERS® World Business Markets Sustainability Legal Breakingviews More

World

Fact check: "Drunk" Nancy Pelosi video is manipulated

By **Reuters**

August 3, 2020 7:23 PM GMT+2 · Updated 4 years ago

Aa

U.S. Speaker of the House Nancy Pelosi, joined by Senate Minority Leader Chuck Schumer, speaks to reporters in the U.S. Capitol in Washington, U.S. July 29, 2020. REUTERS/Erin Scott *Purchase Licensing Rights*

A video circulating on social media shows House Speaker Nancy Pelosi speaking in a slurred and awkward manner. One popular post boasts 91,000 shares on Facebook and bears a caption reading: "This is unbelievable, she is blowed out of her mind, I bet this gets taken down!" The video, however, has been manipulated to make Pelosi appear drunk and incoherent.

A viral example of the video is visible here .

Storia dei deepfake: Software disponibili [13]

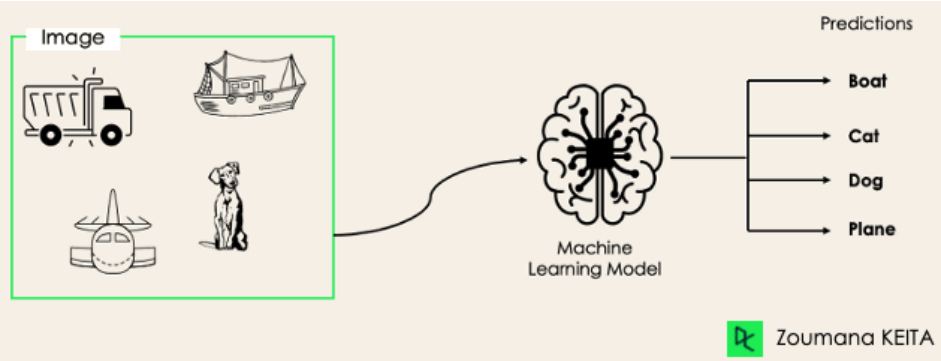
Tool	Type	Reference/Developer	Technique
Cheap fakes			
Adobe Premiere	Commercial Desktop Software	Adobe	Audio Video Editing, AI-powered video reframing
Corel VideoStudio	Commercial Desktop Software	Corel	Proprietary AI
Lip-sync			
dynalips	Commercial Web App	www.dynalips.com/	Proprietary
crazytalk	Commercial Web App	www.reallusion.com/crazytalk/	Proprietary
Wav2Lip	Open source implementation	github.com/Rudrabha/Wav2Lip	GAN with pre-trained discriminator network and visual quality loss function
Facial Attribute Manipulation			
FaceApp	MobileApp	FaceApp Inc	Deep generative CNNs
Adobe	Commercial Desktop Software	Adobe	DNNs + filters
Rosebud	Commercial Web App	www.rosebud.ai/	Proprietary AI
Face Swap			
ZAO	Mobile app	Momo Inc	Proprietary
REFACE	Mobile app	Neocortext, Inc	Proprietary
Reflect	Mobile app	Neocortext, Inc	Proprietary
Impressions	Mobile app	Synthesized Media, Inc.	Proprietary
FakeApp	Desktop App	www.malavida.com/en/soft/fakeapp/	GAN
FaceSwap	Open source implementation	faceswapweb.com/	Employed two pairs of encoder-decoder. Shared encoder parameters.
DFaker	Open source implementation	github.com/dfaker/df	For face reconstruction DSSIM loss function [34] is utilized. Keras library-based implementation.
DeepFaceLab	Open source implementation	github.com/iperov/DeepFaceLab	- provide several face extraction methods, e.g. dlib, MTCNN, S3FD etc. - Extend different Faceswap model i.e. H64, H128, LIAEF128, SAE [33].
FaceSwapGAN	Open source implementation	github.com/shaoanlu/faceswap-GAN	Uses two loss functions namely adversarial loss and perceptual loss to the auto-encoder.
DeepFake-tf	Open source implementation	github.com/StromWine/DeepFake-tf	Same as DFaker however, used tensor-flow for implementation.
Faceswapweb	Commercial Web App	faceswapweb.com/	GAN
Face Reenactment			
Face2Face	Open source implementation	web.stanford.edu/~zollhoef/papers/CVPR2016_Face2Face/page.html	Uses 3DMM and ML technique
Dynamixyz	Commercial Desktop Software	www.dynamixyz.com/	Machine-learning
FaceIT3	Open source implementation	github.com/alew3/faceit_live3	GAN
Face Generation			
Generated Photos	Commercial Web App	generated.photos/	StyleGAN
Voice Synthesis			
Overdub	Commercial Web App	www.descript.com/overdub	Proprietary (AI based)
Respeecher	Commercial Web App	www.respeecher.com/	Combined traditional digital signal processing algorithms with proprietary deep generative modeling techniques
SV2TTS	Open source implementation	github.com/CorentinJ/Real-Time-Voice-Cloning	LSTM with Generalized end-to-end loss
ResembleAI	Commercial Web App	www.resemble.ai/	Proprietary (AI based)
Voicery	Commercial Web App	www.voicery.com/	Proprietary AI and deep learning
VoiceApp	Mobile app	Zoezi AB	Proprietary (AI-based)

Fondamenti teorici/computazionali

Reti neurali [15, 14, 9]

Distribuzione di probabilità condizionata - idea

Abbiamo una serie di record che contengono delle variabili input (dimensione del fiore, colore etc..) e una variabile di output (caso semplice, può essere generalizzato). Non sappiamo a priori come input e output siano legati (altrimenti avremmo risolto il problema !), ma siamo interessati a trovare una funzione di probabilità che associ degli input a degli output. $p(y = c|\mathbf{x}; \theta) = f_c(\mathbf{x}; \theta)$



Reti neurali [15, 14, 9]

Regressione lineare

$$f(x;\theta) = b + wx$$

Regressione polinomiale

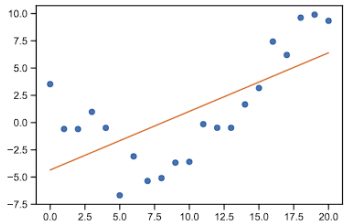
$$f(\mathbf{x};\mathbf{w}) =$$
$$w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_2^2$$

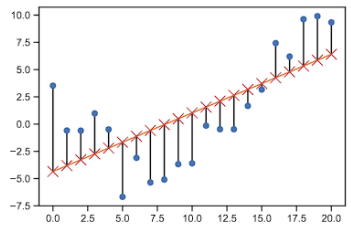
Non-linear feature extraction

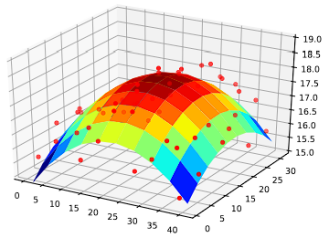
$$f(\mathbf{x};\mathbf{w};\mathbf{V}) = w^T \phi(\mathbf{x};\mathbf{V})$$

Deep neural network

$$f(\mathbf{x};\theta) = f_L(f_{L-1}(...(f_1(x))...)$$







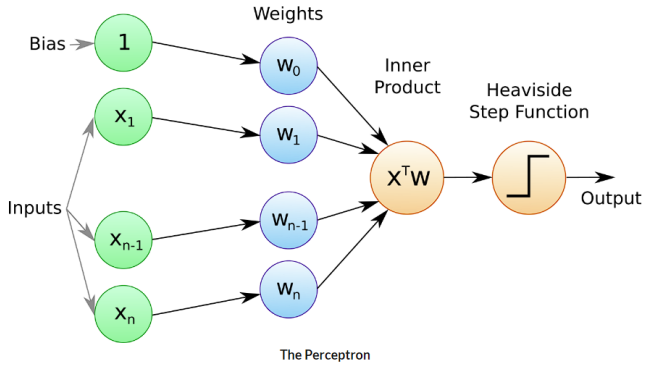
No free lunch theorem

Non esiste un modello che abbia performance migliori in tutti i casi possibili. Ciò è dovuto al fatto che ogni modello fa delle assunzioni.

Reti neurali [15, 14]

Perceptrons

$$
\begin{aligned}
f(\mathbf{x};\theta) &= \\
&= 1(\mathbf{w}^T\mathbf{x} + b \geq 0) \\
&= H(\mathbf{w}^T x + b)
\end{aligned}
$$

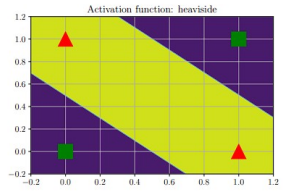


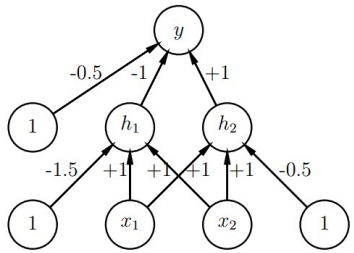
MLP

$$z_l = f_l(z_{l-1}) = \varphi(\mathbf{b}_l + \mathbf{W}_l z_{l-1})$$

$$z_{kl} = \varphi_l\left(b_{kl} + \sum_{j=1}^{K_{l-1}} w_{lkj} z_{jl-1}\right)$$

$$a_l = b_l + \mathbf{W}_l \mathbf{z}_{l-1}$$

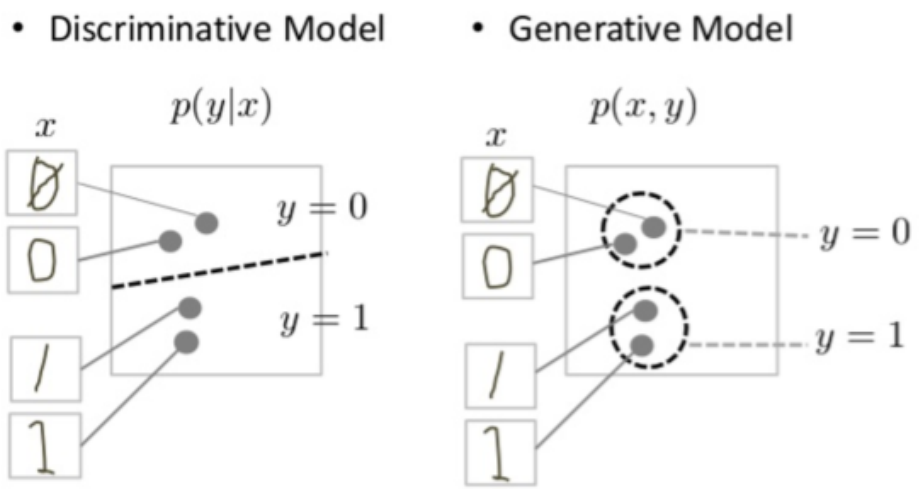




Modelli generativi [10, 15, 14]

Modello generativo

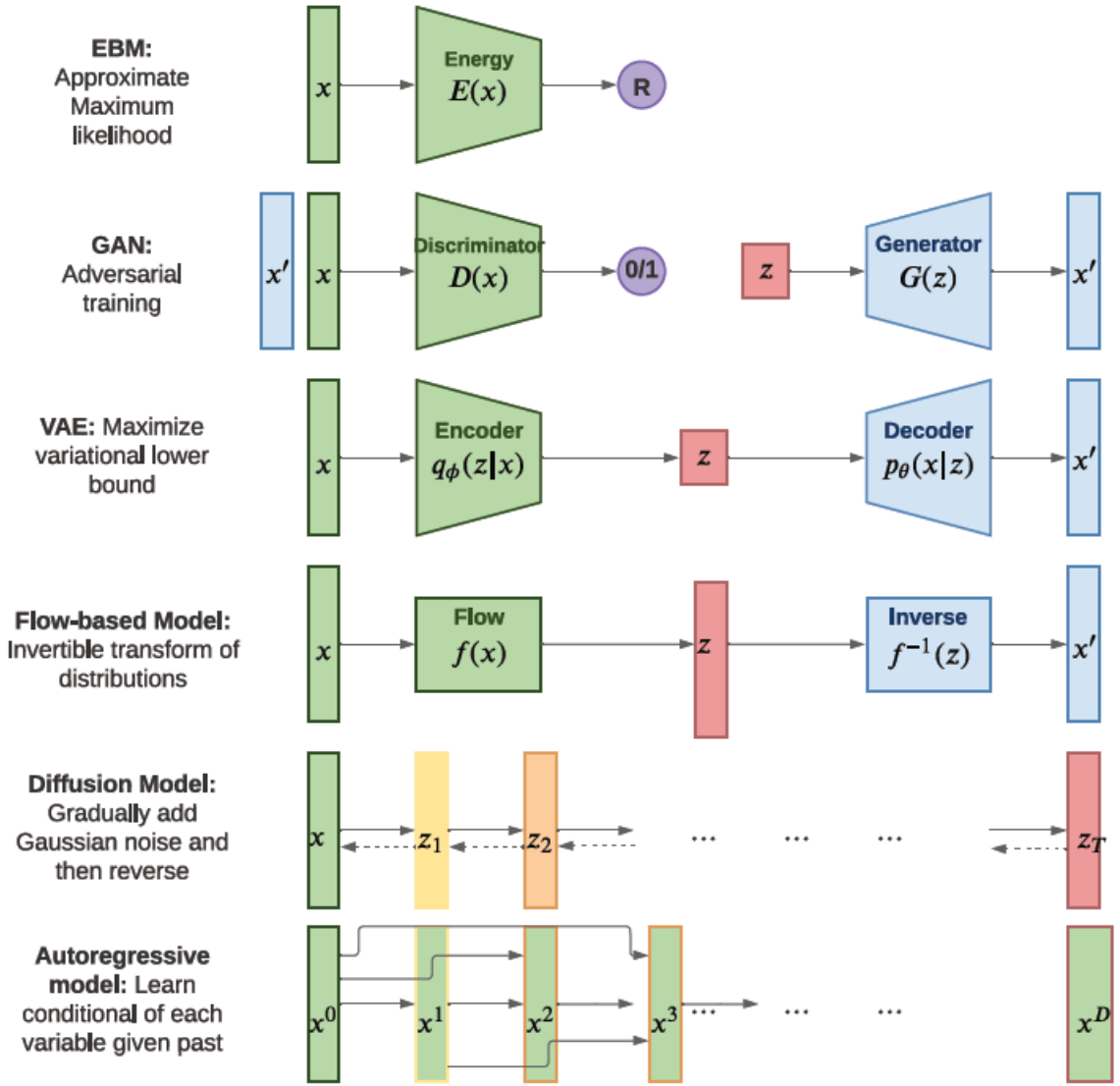
Un modello generativo descrive come viene generato un set di dati utilizzando un modello probabilistico ($p(x) \quad x \in X$). Campionando da questo modello, siamo in grado di generare nuovi dati.



Tipologia di modelli generativi

- Deep generative models (DGM): viene usata una deep neural network. Comprende i Variational Autoencoder (VAE) e le Generative adversarial network oltre che, ad esempio, i Diffusion models e gli Energy based models (EBM)
- Probabilistic graphical models: viene usato un grafo causale

Modelli generativi [15, 14]



Modelli generativi: esempi [15, 14]

Autoencoders [15, 14]

Autoencoder

Encoder (f_e) + Decoder f_d

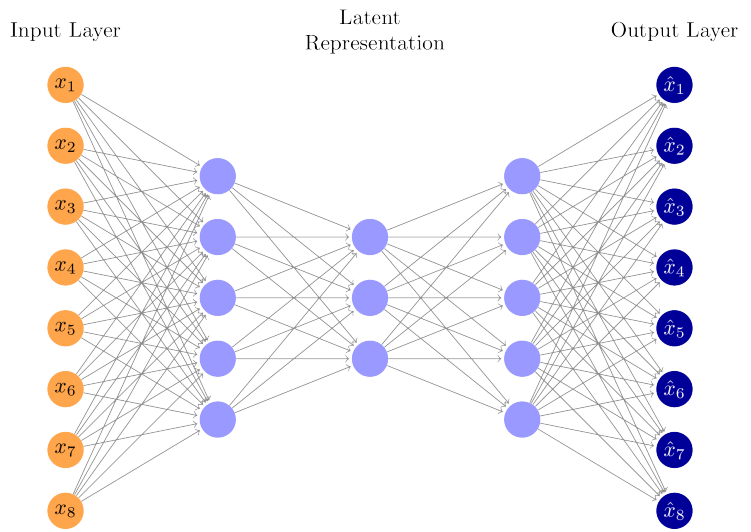
$f_e : x \rightarrow z$ $f_d : z \rightarrow x$

$r(x) = f_d(f_e(x))$ (rec. function)

$\mathcal{L}(\theta) = \|r(x) - x\|^2$ (loss function)

Funzionamento

L'unità in mezzo agisce come collo di bottiglia tra l'input e la sua ricostruzione, in modo da applicare una compressione.



Autoencoders [15]

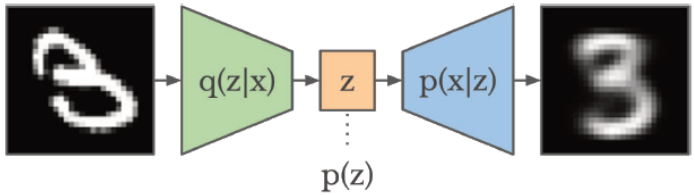
Variational autoencoders [15, 14]

Modello generativo

Un modello generativo descrive come viene generato un set di dati utilizzando un modello probabilistico ($p(x) \quad x \in X$). Campionando da questo modello, siamo in grado di generare nuovi dati.

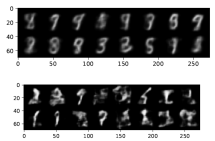
Differenza rispetto agli AE

Rispetto agli autoencoder i variational autoencoder possono essere visti come una versione probabilistica di un autoencoder deterministico. In questo modo si può avere una IA generativa



Remark

La VAE, per come è costruita, è in grado di convertire punti casuali in output, mentre il decoder di AE (deterministico) funziona solo per un punto che è già presente nel training.



VAR generation [15, 14]

Generative adversarial networks [15, 14]

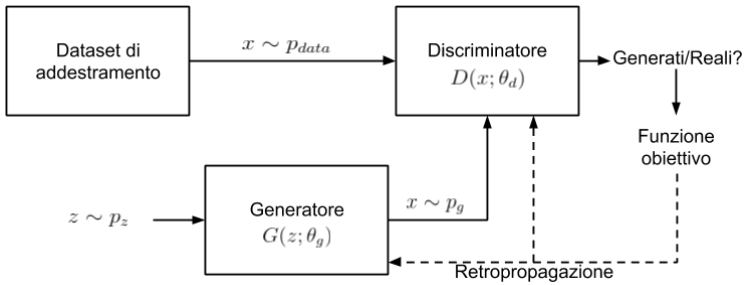
Idea

Ho due reti neurali

- Generatore: creare nuovi dati
- Discriminatore: distinguere i dati nuovi da quelli veri

Apprendimento

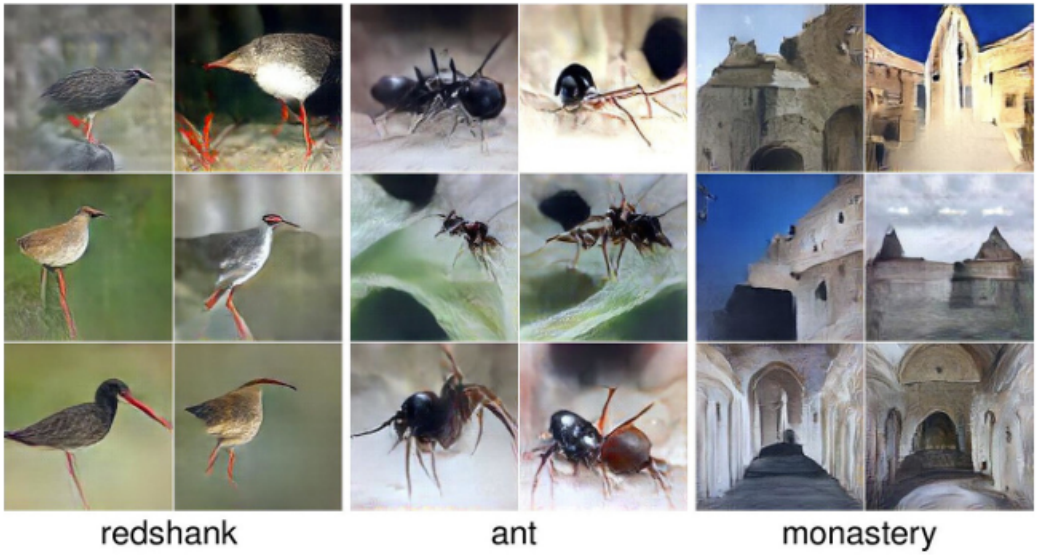
$$\min_G \max_D E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$



Algorithm 26.2: GAN training algorithm

Initialize ϕ, θ
for *each training iteration* **do**
  for K *steps* **do**
    Sample minibatch of M noise vectors $z_m \sim q(z)$
    Sample minibatch of M examples $x_m \sim p^*(x)$
    Update the discriminator by performing stochastic gradient descent using this gradient:
    $\nabla_\phi \frac{1}{M} \sum_{m=1}^{M} [g(D_\phi(x_m)) + \nabla_\phi h(D_\phi(G_\theta(z_m)))]$.
  Sample minibatch of M noise vectors $z_m \sim q(z)$
  Update the generator by performing stochastic gradient descent using this gradient:
  $\nabla_\theta \frac{1}{M} \sum_{m=1}^{M} l(D_\phi(G_\theta(z_m)))$.
Return ϕ, θ

VAR generation [16]



Difesa: come rilevarle ?

Metodi [13]

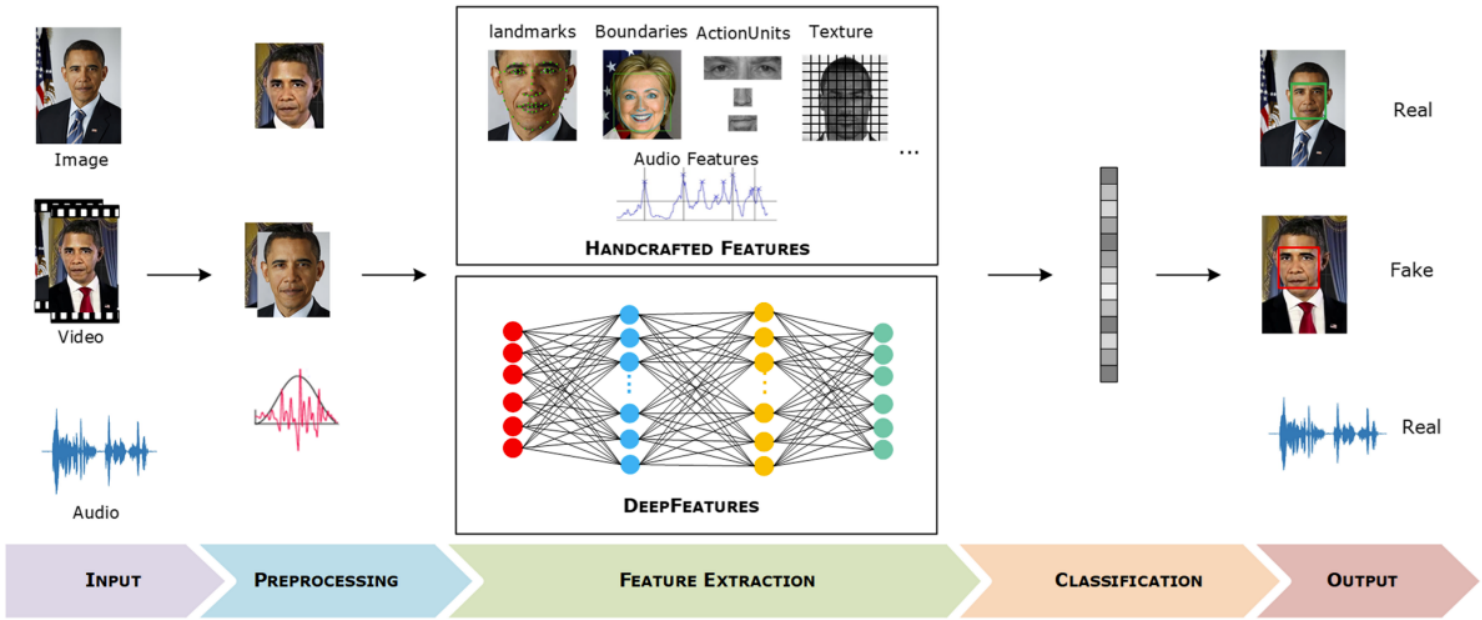
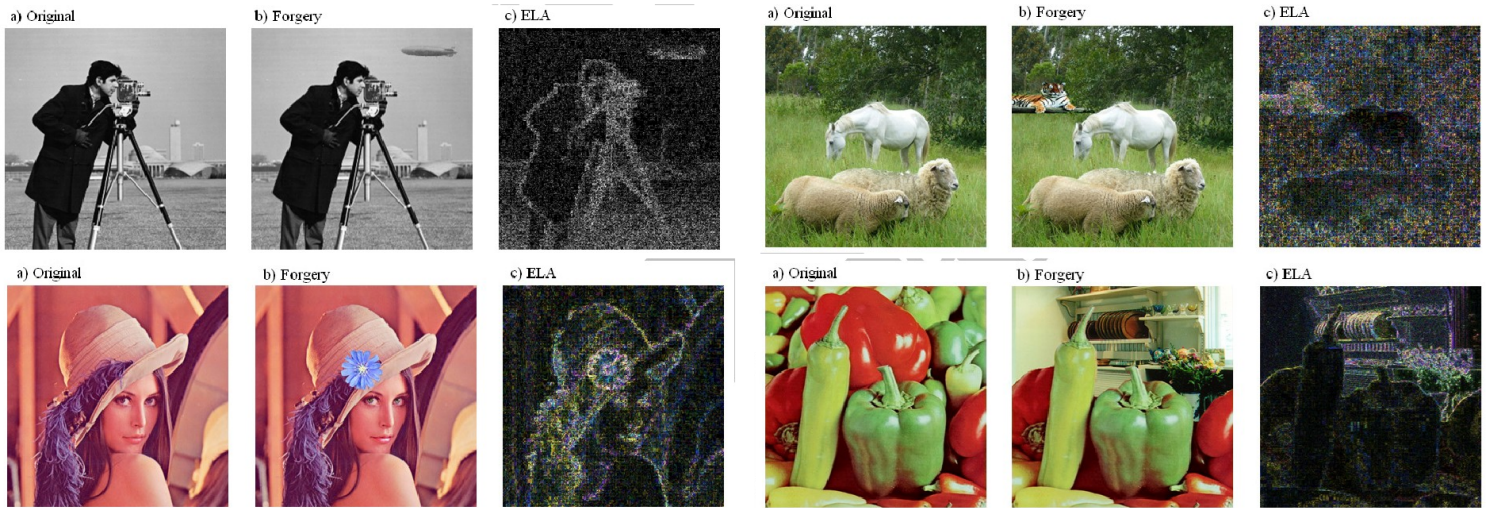
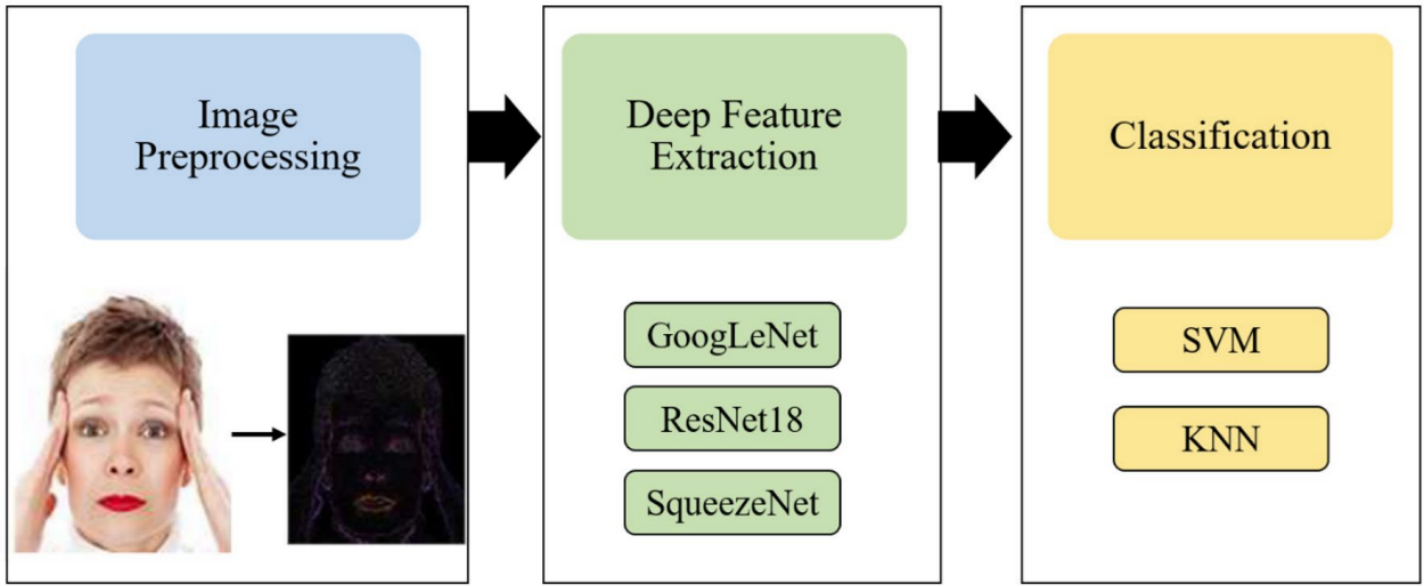


Image
Video
Audio
landmarks
Boundaries
ActionUnits
Texture
Audio Features
HANDCRAFTED FEATURES
DEEPFEATURES
Real
Fake
Real
INPUT
PREPROCESSING
FEATURE EXTRACTION
CLASSIFICATION
OUTPUT

Error level analysis [12]



Error level analysis + Deep Learning [17]



Aspetti legali

IA act, 2024

70a) A variety of AI systems can generate large quantities of synthetic content that becomes increasingly hard for humans to distinguish from human-generated and authentic content. The wide availability and increasing capabilities of those systems have a significant impact on the integrity and trust in the information ecosystem, raising new risks of misinformation and manipulation at scale, fraud, impersonation and consumer deception. **In the light of those impacts, the fast technological pace and the need for new methods and techniques to trace origin of information, it is appropriate to require providers of those systems to embed technical solutions that enable marking in a machine readable format and detection that the output has been generated or manipulated by an AI system and not a human.** Such techniques and methods should be sufficiently reliable, interoperable, effective and robust as far as this is technically feasible, taking into account available techniques or a combination of such techniques, such as watermarks, metadata identifications, cryptographic methods for proving provenance and authenticity of content, logging methods, fingerprints or other techniques, as may be appropriate

Conseguenze di un uso improprio dei deepfake [11]

Uso improprio dei deepfake

- Diffamazione, attraverso la creazione di contenuti che denigrano o danneggiano la reputazione di un individuo
- Furto di identità, che rileva nel caso della creazione di video o audio in cui un soggetto viene rappresentato come un'altra persona
- Violazione della privacy, attraverso la condivisione non consensuale di informazioni relative a una persona

Bibliography I

[1] https://www.nsa.gov/Press-Room/Press-Releases-Statements/Press-Release-View/Article/3523329/nsa-us-federal-agencies-advise-on-deepfake-threats/.

[2] https://csrc.nist.gov/topics/technologies/artificial-intelligence.

[3] https://journals.ametsoc.org/view/journals/bams/103/5/BAMS-D-20-0234.1.xml.

[4] https://www.researchgate.net/figure/A-biological-neuron-in-comparison-to-an-artificial-neural-network-a-human-neuron-b_fig2_339446790.

[5] https://www.nationalgeographic.com/photography/article/digitally-manipulated-ai-altered-photo-images.

Bibliography II

[6] https://www.historyofinformation.com/detail.php?id=4792.

[7] https://www.reuters.com/article/idUSKCN24Z2B1/.

[8] https://www.wsj.com/articles/fraudsters-use-ai-to-mimic-ceos-voice-in-unusual-cybercrime-case-11567157402.

[9] https://www.datacamp.com/blog/classification-machine-learning.

[10] https://developers.google.com/machine-learning/gan/generative?hl=it.

[11] .

Bibliography III

[12] Daniel Cavalcanti Jeronymo, Yuri Cassio Campbell Borges e Leandro dos Santos Coelho. "Image forgery detection by semi-automatic wavelet soft-thresholding with error level analysis". In: *Expert Systems with Applications* 85 (2017), pp. 348–356.

[13] Momina Masood et al. "Deepfakes generation and detection: State-of-the-art, open challenges, countermeasures, and way forward". In: *Applied intelligence* 53.4 (2023), pp. 3974–4026.

[14] Kevin P. Murphy. *Probabilistic Machine Learning: Advanced Topics*. MIT Press, 2023. URL: http://probml.github.io/book2.

[15] Kevin P. Murphy. *Probabilistic Machine Learning: An introduction*. MIT Press, 2022. URL: probml.ai.

Bibliography IV

[16] Anh Nguyen et al. “Plug & play generative networks: Conditional iterative generation of images in latent space”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 4467–4477.

[17] Rimsha Rafique et al. “Deep fake detection and classification using error-level analysis and deep learning”. In: *Scientific Reports* 13.1 (2023), p. 7422.