

Internship Report
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Pembimbing Ilham Imaduddin

Outline

- 1. Pendahuluan
- 2. Aplikasi Nodeflux
- 3. Teknologi Nodeflux
- 4. Proyek Penelitian
- 5. Proyek Penelitian: Streaming
- 6. Proyek Penelitian: Inferencing
- 7. Hasil penelitian

Pendahuluan

Nodeflux:

- Perusahaan berbasis kecerdasan buatan (AI) untuk melakukan analisis video dari instrumen kamera konvensional.
- Perusahaan pertama di Indonesia yang bergerak di bidang Intelligence Video Analytics (IVA).
- Satu-satunya perusahaan di Indonesia yang masuk ke NVIDIA Inception Program (Akselerator untuk Al dan Deep Learning).
- Perusahaan teknologi rintisan baru (startup), dirintis 2016.
- Sudah digunakan oleh Kepolisian RI, Badan Intelijen Negara (BIN), Jasa Marga,
 Transjakarta, Jakarta Smart City, Bandung Command Center, GOJEK dll

Aplikasi Nodeflux

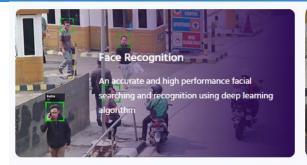


Jokowi juga mencoba face recognition Nodeflux. Nama dan jabatan Jokowi langsung terlihat ketika wajahnya terdeteksi kamera. Sistem pengenal wajah yang terkoneksi dengan data penduduk dan catatan sipil alias dukcapil ini sudah digunakan sejak penyelenggaraan Asian Games. (chri/end)

Teknologi:

- Sumber video dari kamera CCTV.
- Analisis video berbasis jaringan syaraf tiruan (Artificial Neural Network) dengan ratusan layer (Deep Neural Network) yang dikovolusikan (Convolutional Neural Network).
- Model AI dilatih dan diinferensikan pada NVIDIA GPU (Graphics Processing Unit) .
- Model AI dapat diinferensikan secara offline ataupun online.
- Hasil analisis ditampilkan di halaman web.

Intelligent Video Analytics







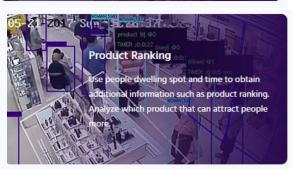








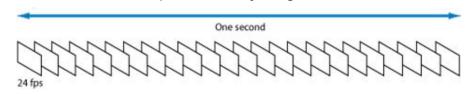


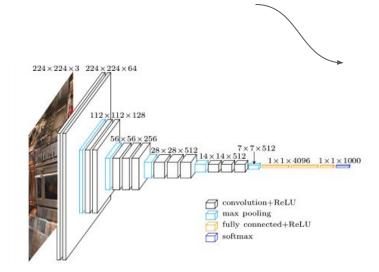




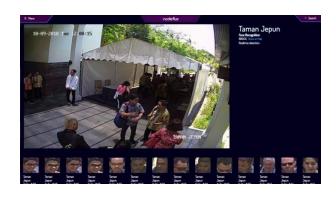
1. Video direkam kamera CCTV

2. Video dipecah menjadi gambar

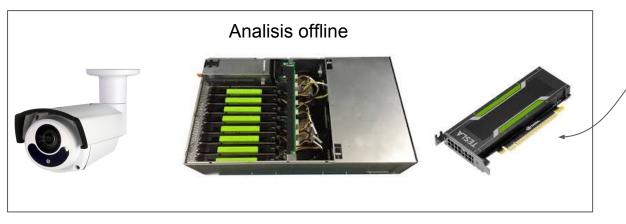




3. Gambar dianalisis dengan model Deep Learning.



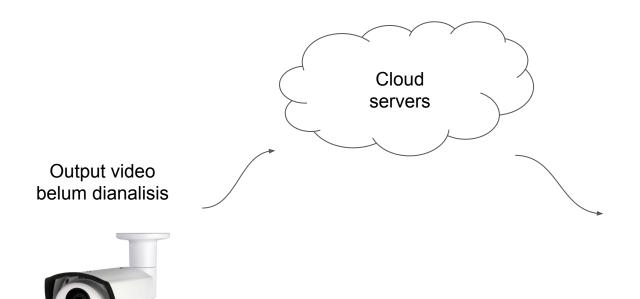
4. Hasil analisis ditampilkan di web.



Analisis video dengan GPU (NVIDIA Tesla P4/P40)

Output video Sudah dianalisis



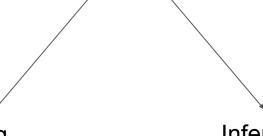


Output video sudah dianalisis



Proyek Penelitian

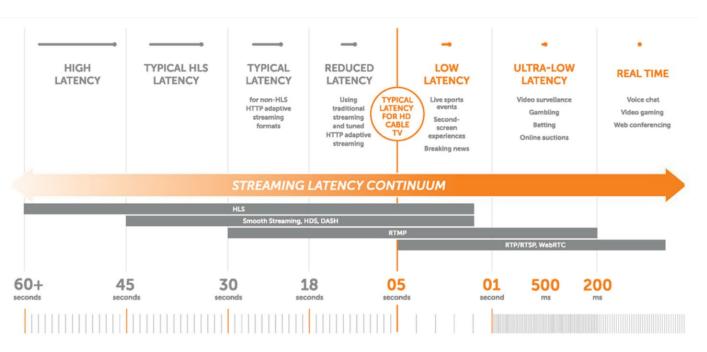
Object Detection Inferencing Streaming Berbasis Artificial Neural Network



Streaming (mengalirkan data)

Inferencing (mendapatkan hasil analisis dari data)

Proyek Penelitian: Streaming



Protokol

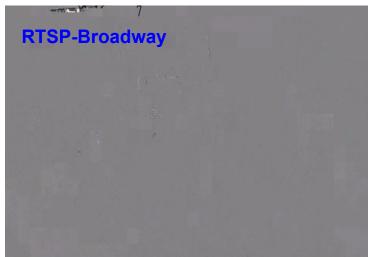
- DASH
- RTP/RTSP
- WebRTC

Decoder

- JSMPEG (Codec: MPEG-1)
- Broadway.js (Codec: H264)
- OGV.js
 - (Codec: OGG Vorbis)
- Shaka Player (Codec: H264)

Pemrograman

Python dan Javascript



DASH-Shaka Player





Decoder	JSMPEG	BROADWAY	OGV	SHAKA	HTML5
Protokol	RTSP	RTSP	RTSP	DASH	WebRTC
Codec	MPEG-1	H264	OGG Vorbis	H264	-
Realtime	Ya	Tidak	Tidak	Tidak	Ya
Analisis Lainnya	Menggunakan WebSocket Relay, Kompatibilitas browser baik	H264 decoder dengan Javascript Resource heavy di client.	OGG Vorbis decoder di Javascript, Menggunakan WebAssembly	Adaptive bitrate, Video dikirim dengan referensi dari manifest.mpd	Didesain untuk client-to-client library aiortc. menggunakan negotiation.

Inferensia Object Detection

- Input Video 1280x720 piksel
- Dataset COCO (Common Object In Context)
 (80 Objek, 5 Captions/image)
- Model CNN Pretrained (MobileNet v2)
- Ouput Model Koordinat Bounding Box
- Pemrograman Python dengan TensorFlow
- Inferensia dilakukan pada server (AWS t3.large 2 vCPU, 8 GiB RAM)
- Transmisi frame dilakukan dengan sistem message queue (RabbitMQ dan Redis)

MobileNet

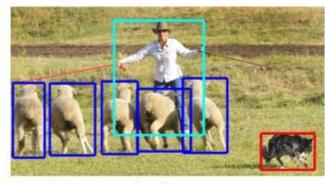
- Arsitektur Convolutional Neural Network
- Didesain untuk mobile phone (Google Pixel) sehingga cocok untuk resource komputasi yang minim.
- Memiliki akurasi yang relatif tinggi apabila dibandingkan dengan Multiply Add Computation (MAC) yang rendah.
- Filter konvolusi dibagi menjadi depthwise dan pointwise.
- Blok Layer menggunakan Batchnorm (BN) dan Activation Function Rectified Linear Unit (ReLU)



(a) Image classification



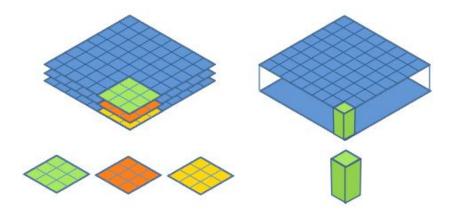
(c) Semantic segmentation



(b) Object localization

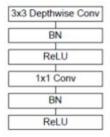


(d) This work



Depthwise Convolutional Filters

Pointwise Convolutional Filters

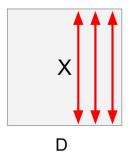


Depthwise Separable Convolution

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size	
Conv/s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$	
Conv dw/s1	$3 \times 3 \times 32 \text{ dw}$	$112 \times 112 \times 32$	
Conv/s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$	
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$	
Conv/s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$	
Conv dw / s1	$3 \times 3 \times 128 \mathrm{dw}$	$56 \times 56 \times 128$	
Conv/s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$	
Conv dw / s2	$3 \times 3 \times 128 \mathrm{dw}$	$56 \times 56 \times 128$	
Conv/s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$	
Conv dw / s1	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$	
Conv/s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$	
Conv dw / s2	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$	
Conv/s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$	
5× Conv dw/s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$	
Onv/sl	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$	
Conv dw / s2	$3 \times 3 \times 512 \text{ dw}$	$14 \times 14 \times 512$	
Conv/s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$	
Conv dw / s2	$3 \times 3 \times 1024 \text{ dw}$	$7 \times 7 \times 1024$	
Conv/s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$	
Avg Pool / s1	Pool 7 × 7	$7 \times 7 \times 1024$	
FC/s1	1024×1000	$1 \times 1 \times 1024$	
Softmax / s1	Classifier	$1 \times 1 \times 1000$	

N



1. compute the empirical mean and variance independently for each dimension.

2. Normalize

$$\widehat{x}^{(k)} = \frac{x^{(k)} - E[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}$$

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\};$

Parameters to be learned: γ , β

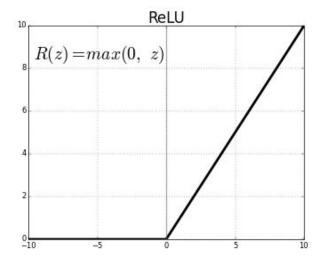
Output: $\{y_i = BN_{\gamma,\beta}(x_i)\}$

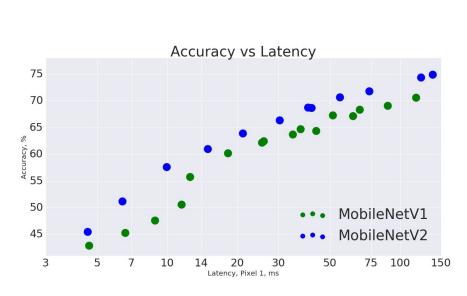
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} x_{i} \qquad // \text{ mini-batch mean}$$

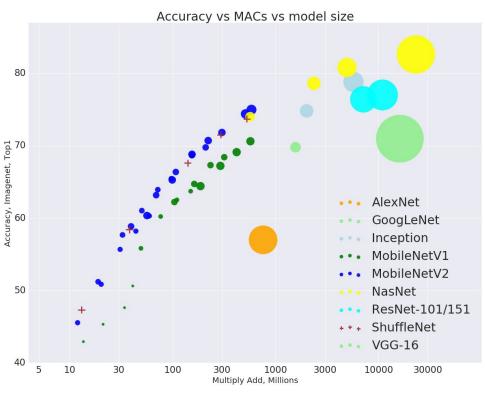
$$\sigma_{\mathcal{B}}^{2} \leftarrow \frac{1}{m} \sum_{i=1}^{m} (x_{i} - \mu_{\mathcal{B}})^{2} \qquad // \text{ mini-batch variance}$$

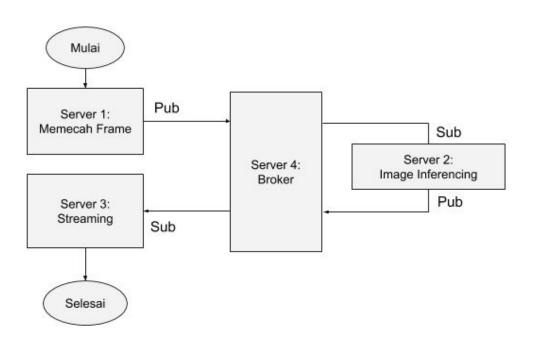
$$\widehat{x}_{i} \leftarrow \frac{x_{i} - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^{2} + \epsilon}} \qquad // \text{ normalize}$$

$$y_{i} \leftarrow \gamma \widehat{x}_{i} + \beta \equiv \text{BN}_{\gamma,\beta}(x_{i}) \qquad // \text{ scale and shift}$$









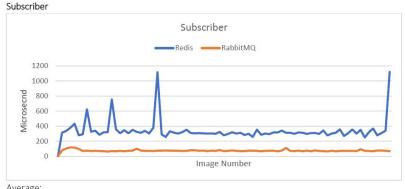
Connected

Redis Streamer Client



RabbitMQ Streamer Client





Average:

Average: Redis

RabbitMQ

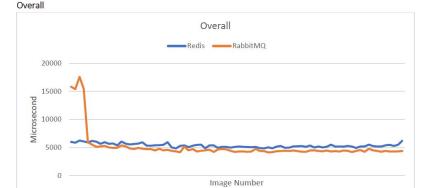
Redis

: 339,78 μs (+265,80 μs)

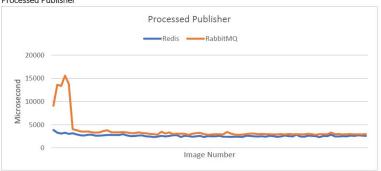
: 5.371,44 µs (+818,68 µs)

: 4.552,76 µs

RabbitMQ : 73,98 µs



Processed Publisher



Average:

Redis : 2.630,61 µs

: 3.726.87 µs (+1.096,26 µs) RabbitMQ

Akurasi: 75%

Parameter: 6,06 Juta

Waktu Rata-rata/frame:

- 5,371ms (Redis)
- 4,552ms (RabbitMQ)

Waktu Tertunda (Delay):

- 161,31ms (Redis)
- 136,56ms (RabbitMQ)

Referensi

- Microsoft COCO: Common Objects in Context (https://arxiv.org/pdf/1405.0312.pdf)
- MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications (https://arxiv.org/pdf/1704.04861.pdf)
- MobileNetV2: Inverted Residuals and Linear Bottlenecks (https://arxiv.org/pdf/1801.04381.pdf)
- A Survey of Distributed Message Broker Queues (https://arxiv.org/pdf/1704.00411.pdf)
- MobileNet: Deteksi Objek pada Platform Mobile
 (https://medium.com/nodeflux/mobilenet-deteksi-objek-pada-platform-mobile-bbbf3806e4b3)
- 6. Convolutional Neural Networks (http://cs231n.github.io/convolutional-networks/)

