20 BÖLÜM

BÜYÜK VERİ VE BİYOİSTATİSTİĞİN ACİL TIPTA YAPAY ZEKÂ SÜREÇLERİNE ETKİSİ

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GİRİŞ

Son yıllarda sağlık hizmetlerinde dijitalleşmenin artmasıyla birlikte, büyük veri ve yapay zekâ (YZ) uygulamaları klinik karar destek sistemlerinde önemli bir yer edinmiştir. Özellikle acil tıp gibi zamanın kritik olduğu ve hasta yoğunluğunun yüksek seyrettiği alanlarda bu teknolojiler klinik süreçlerin verimliliğini artırmaktadır (1,2).

Büyük veri, hacim (volume), çeşitlilik (variety), hız (velocity), doğruluk (veracity) ve değer (value) olmak üzere beş temel boyutta tanımlanır (3). Sağlık alanında büyük veri elektronik sağlık kayıtları, tıbbi görüntüler, genomik bilgiler, sensör verileri, hasta raporları ve sosyal medya gibi çeşitli kaynaklardan sağlanmaktadır (4). Bu veri yığınları, doğru analiz edilmediğinde sadece bir bilgi kalabalığı oluştururken uygun biyoistatistiksel yöntemler ve makine öğrenimi algoritmaları sayesinde anlamlı klinik sonuçlara dönüştürülebilir (5).

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uzun-kısa vadeli bellek (LSTM) ağları ve hibrit modeller; hasta ciddiyeti belirleme, triyaj sınıflaması, klinik sonuç öngörüsü ve hastane yatışı tahmininde yüksek doğruluk oranlarıyla öne çıkmaktadır.

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